Effects of Wildfire on Vegetation Composition and Structure in Linville Gorge Wilderness Area, North Carolina

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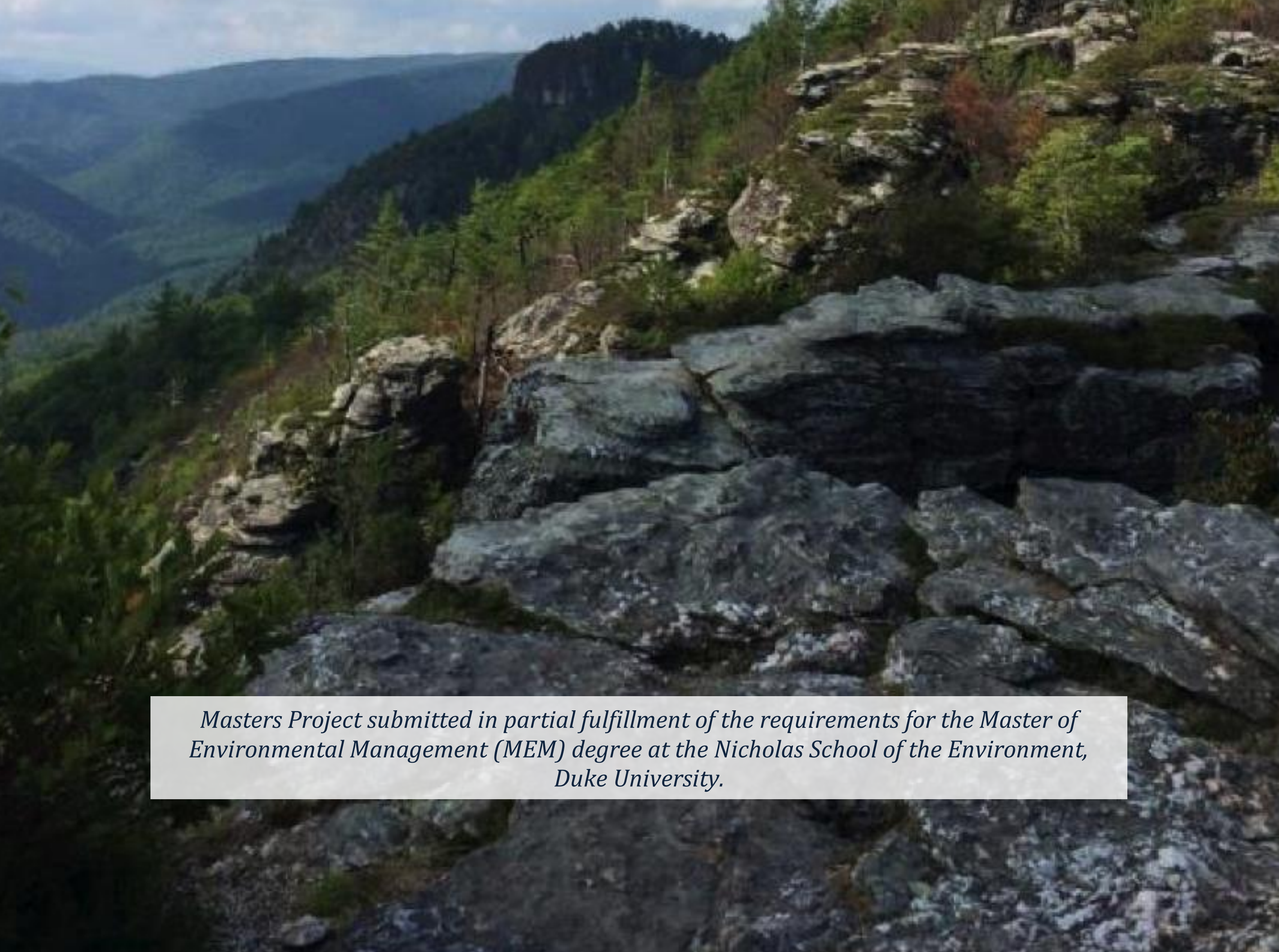

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Executive Summary

Located in Western North Carolina, Linville Gorge Wilderness Area has an extensive fire history that has been characterized by burns of variable size and severity. Beginning in the 1940s, an era of burn suppression policies curtailed the Gorge's established fire regime. Local stakeholders, including The Wilderness Society (TWS) and the U.S. Forest Service, are concerned about the effects of burn suppression on fire dependent species and communities. As such, these groups are interested in following a modern resurgence of anthropogenic wildfires with a prescribed fire program.

Many sampling efforts since 1992 have studied permanent vegetation plots spread throughout Linville Gorge to characterize local plant communities and their relationship with five recent fires. With my Master's Project, done for The Wilderness Society, two objectives related to fire in the Gorge are addressed. First, structural and compositional trends in Linville Gorge forests have been identified, and those trends have been overlain with geospatial environmental variables as well as remotely sensed fire severity estimations. Second, wildfires have been evaluated for their meeting of restoration goals. TWS's restoration targets include a reduction in the importance of ericaceous and fire intolerant species, an increase in the importance of fire dependent species, and a lack of invasion from nonnative species following fire events. Multivariate statistical methods have been implemented to analyze the Linville vegetation dataset for structural and compositional trends, and paired t-tests have been utilized to evaluate changes in target species' importance with fire.

Fire has emerged as a major driver of change and compositional heterogeneity in the Wilderness Area. However, burns have produced variable success in meeting restoration goals. While ericaceous species have been reduced in importance, fire dependent species also have experienced declines. Fire intolerant species have increased in abundance with fire; similar increases have not been observed on unburned plots. Invasive species may be a concern, particularly in twice burned forests. If prescribed fire is pursued as a restoration tool in Linville Gorge Wilderness Area, managers should be careful in planning the frequency and severity of fires, and continue to monitor results for the achievement of goals.

Key Words: Southern Appalachia, Linville Gorge Wilderness Area, The Wilderness Society, Table Mountain Pine, vegetation composition and structure, prescribed fire, fire monitoring, forest restoration, GIS, Landsat, dNBR, nonmetric multidimensional scaling

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Introduction

Southern Appalachian forests have an extensive fire history and are home to a diversity of fire-adapted species. Ridges are dominated by fire-dependent pine species (e.g. *Pinus pungens* and *Pinus rigida*), the regeneration of which is facilitated by open-canopy, duff-free conditions (Barden & Woods 1976). These species have serotinous cones, thick fire-resistant bark, and can sprout basally after disturbance (Weakley 2010). Fire also is thought to have contributed significantly to the maintenance and regeneration of oak forests (Arthur et al. 1998).

Before the introduction of humans, lightning strikes were major drivers of landscape heterogeneity in Southern Appalachia (Van Lear & Waldrop 1989). However, the Holocene fire regime has been marked by anthropogenic influences. Charcoal evidence suggests that, in pre-Columbian Southern Appalachia, fires burned regularly on xeric pine-oak sites for the last 4,000 years and on mesic hardwood sites for 2,000 years. On both site types, abrupt increases in fire frequency characterized the past 1,000 years, which coincided with the appearance of Woodland Tradition Native Americans (Fesenmeyer & Christensen 2010). Studies have suggested that Native Americans employed fire as a landscape management tool, which in turn drove community composition increasingly toward fire-dependent species (Delcourt & Delcourt 1997; Nowacki & Abrams 2008) and elevated the importance of oak-chestnut forests throughout Southern Appalachia (Delcourt & Delcourt 1998).

Fire frequency has declined dramatically over the past 250 years (Fesenmeyer & Christensen 2010). Particularly since the 1940s, suppression has been a prevailing fire control method (Harrod & White 1999). Xeric pine-hardwood ecosystems have been impacted heavily by the fire suppression practices (Vose et al. 1999). In the absence of regular burns, increased competition, herbivory, and acorn predation have contributed to the decline of oak species (Arthur et al. 1998). Fire-dependent pine species too have been reduced in importance (Barden & Woods

1976). Conversely, fire-sensitive species such as *Acer rubrum* and *Nyssa sylvatica* have swelled in abundance (Arthur et al. 1998).

Area experts hypothesize that the era of fire suppression also has contributed to the increasing understory dominance and range expansion of broadleaf evergreen vegetation, particularly of ericaceous species (Robert Peet PhD, University of North Carolina, personal communication). Concurrent die-back of dominant overstory species has worsened the effects of fire suppression. Canopy gaps due to the *Castanea dentata* and *Tsuga canadensis* disease- and pest-induced declines have encouraged denser, more homogeneous thickets of *Rhododendron maximum*, *Kalmia latifolia*, and other ericaceous shrubs (Webster *et al.*, 2012). There is growing concern that this observed range extension of ericaceous shrubs, especially those such as *Rhododendron maximum* that are typically confined to riparian areas and bottomlands, has been suppressing the propagation of desirable upland deciduous species (e.g. *Quercus* and *Pinus* species) (Hugh Irwin, The Wilderness Society Landscape Conservation Planner, personal communication).

Natural fires have not provided adequate ignitions to offset fire suppression policies. For recent fires that have burned throughout Southern Appalachia, lightning strike ignitions have accounted for only a small portion of wildfire starts (Barden 1974; Bratton & Meier 1998). Because strikes are most probable during the wettest months (Barden 1974), lightning-ignited fires often are not severe enough to encourage pine regeneration (Barden & Wood 1976). Successional changes due to fire suppression may have reduced the flammability and, accordingly, further decreased the probability of natural fire (Nowacki & Abrams 2008). In the event of isolated or infrequent burns, Van Lear and Waldrop (1989) found that single fires did little to reduce understory competition, and could have stimulated the sprouting of fire-intolerant species.

Considering these trends, prescribed fire regimes are increasingly necessary to maintain Southern Appalachian pine-hardwood forests (Waldrop & Goodrick 2012). In North Carolina, nonprofit organizations including The Wilderness Society (TWS) and The Nature Conservancy as well as the United States Forest Service (USFS) are collaborating to spearhead the reintroduction of regular anthropogenic fire. Of particular interest is Linville Gorge Wilderness Area.

Objectives

The research generated through my Master's Project will help to inform restoration decisions for Linville Gorge Wilderness Area, located in Western North Carolina, by examining changes in vegetation composition and structure within the context of a recent resurgence in anthropogenic wildfire. Impetus for the study is driven by the Collaborative Forest Landscape Restoration Project (CFLRP) for the Grandfather Ranger District. Their leadership team, including the USFS, The Wilderness Society, and others want to see prescribed fire in Linville Gorge. However, a 2012 Forest Service proposal met with significant resistance from hikers and the surrounding housing community. Opponents listed several objections, including the broadness of the plan, the belief that wilderness should be left "untrammeled," and the thought that fire has never been "natural" in the Gorge (Bernard Clark, J.D., lawyer for opposition, personal communication). From my research, the CFLRP hopes to see support for fires restoring some of the Gorge's vegetation communities toward their pre-Columbian states.

The primary client for my research is The Wilderness Society. They are a nation-wide nonprofit organization with a mission "to protect wilderness and inspire Americans to care for our wild places" (http://wilderness.org/). Given their interests in prescribed fire, I have two main objectives for my research:

Objective 1: Identify structural and compositional trends in Linville Gorge Wilderness Area forests, and overlay those trends with environmental and fire severity variables.

Objective 2: Evaluate whether wildfires are meeting TWS's restoration goals for Linville Gorge Wilderness Area. These are:

1. A reduction in the importance of ericaceous species.
2. A reduction in the importance of fire intolerant species.
3. An increase in the importance of fire dependent species.
4. The lack of invasion from nonnative species following fire events.

STUDY AREA AND HISTORICAL WORK

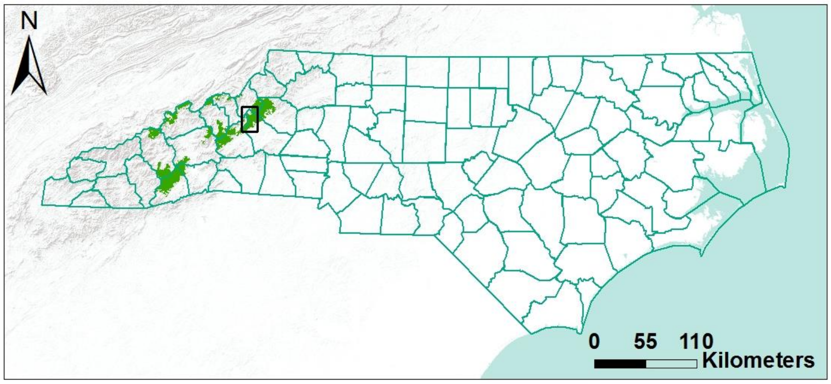

Figure 1a: Location of Linville Gorge Wilderness Area within Pisgah National Forest.

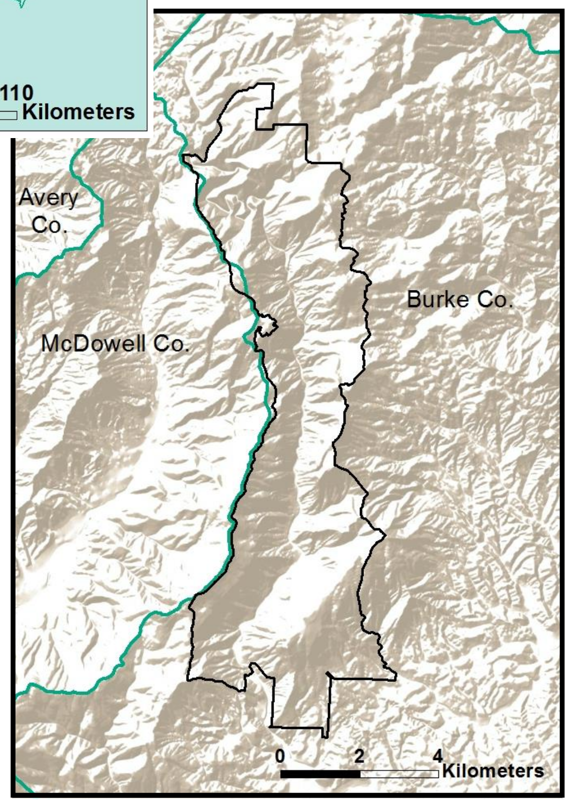

Figure 1b: Linville Gorge Wilderness Area boundary (USFS, unpublished data) that spans NC's Burke and McDowell Counties.

Study Area

Located in Pisgah National Forest of North Carolina, Linville Gorge contains 4,390 hectares of federally designated wilderness area (Figure 1a), much of which is old growth forest (Newell & Peet 1998). Tree cores and scarring in and around the Gorge provide evidence of a variable fire history with catastrophic crown fires occurring in 1860 and 1915; the extent and frequency of co-occurring, lower intensity fires are unknown. Beginning in the 1940s, fire suppression became standard Forest Service practice, causing fuel load accumulation in the understory (Reilly et al. 2006). However, since 2000, anthropogenic wildfires of mixed severity have burned the majority of the Wilderness Area along with surrounding forest (Wimberly & Reilly 2007; Waldrop et al. 2013; USFS, unpublished data).

The boundary of Linville Gorge Wilderness Area borders North Carolina's Burke and McDowell Counties (Figure 1b). Elevation ranges from 820 to 1,250 meters; prominent rock bluffs bisect each side of the Gorge. Linville River flow has been responsible for the erosion of parent material, leaving exposed rock formations. Annual average precipitation falls mostly as rain, is highest in the summer months, and varies from 1,250 to 1,625 millimeters. Because of accessibility limitations, much of the landscape has remained as old growth forest. Pyriscent *Pinus* and *Quercus* species dominate the ridges and bluffs. The slopes are majority *Quercus* and *Acer* species, also with *Nyssa sylvatica* and *Oxydendrum arboretum*, as well as *Kalmia latifolia* and *Vaccinium* species. Moist coves and slopes are populated with large *Tsuga canadensis* and dense *Rhododendron maximum* (Newell & Peet 1998; Reilly et al. 2006).

Seven community types have been identified and described in Linville Gorge Wilderness Area: Xeric Evergreen Forests, Acid Cove and Slope Forests, Montane Oak Forests, Rock Outcrops, Rich Cove and Slope Forests, Alluvial Wetlands, and Rocky Streamside Shrublands (Newell & Peet 1998). Xeric Evergreen, Acid Cove and Slope, and Montane Oak Forests are most common. Of these three, Xeric Evergreen Forests reach the greatest abundance; they occupy xeric slopes above bluffs, moderately to slightly steep slopes on the bluffs, and ridges below bluffs. Typically, they have nutrient-poor, thin soil with low moisture retention capacity. Canopy species include *Pinus pungens, Pinus rigida, Pinus virginiana, Tsuga caroliniana, Quercus montana*, and *Quercus coccinea*, as well as dense evergreen shrubs including *Kalmia latifolia* and *Rhododendron maximum*. Like Xeric Evergreen Forests, Acid Cove and Slope Forests are widely distributed in Linville (Newell 1997). They are found on “narrow gorges, steep ravines, and low gentle ridges within coves” at and below moderate elevations (Schafale & Weakley 1990). Sites are sheltered, relatively infertile, and most plentiful on low elevation slopes. Limited species diversity is characteristic, as is a dense evergreen shrub layer dominated by *Rhododendron maximum*. *Tsuga canadensis, Ilex opaca, Acer rubrum, Quercus montana, Nyssa sylvatica, Oxydendrum arboretum, Pinus strobus, Liriodendron tulipifera,* and *Quercus rubra* are common overstory species. Montane Oak Forests, while common in Southern Appalachia, cover a small area of Linville Gorge. Gneiss bedrock is the predominant substrate; soil usually is more fertile and finer-textured than Xeric Evergreen or Acid Cove and Slope Forests. *Quercus* species, especially *Quercus montana*, dominate the overstory (Newell 1997).

Less common forest types in Linville Gorge Wilderness include Rock Outcrops, Rich Cove and Slope Forests, Alluvial Wetlands, and Rocky Streamside Shrublands. Rock Outcrops have been documented on Linville bluffs and exposed mountain summits; they have infertile soil, steep slopes, and are highly exposed to weather events. *Rhododendron minus* and *Selaginella tortipila*, a species of club moss, commonly occur on Rock Outcrops. Of all community types in the Wilderness Area, Rock Outcrops also contain the highest amount of nationally rare species. Examples include Southern Appalachian endemics such as *Hudsonia Montana* and *Liatris helleri.* Rich Cove and Slope Forests are the most species-rich in Linville Gorge, and occupy nutrient-rich soils. Typical overstory species include *Carya glabra, Acer rubrum, Quercus rubra, Liriodendron tulipifera, Betula lenta,* and *Halesia tetraptera*. Alluvial Wetlands are distributed along stream flats and the Linville River floodplain. *Liquidambar styraciflua*, *Platanus occidentalis*, and *Betula lenta* are major canopy species. Finally, Rocky Streamside Shrublands are limited to open areas on the banks of the Linville River. Common species are *Leucothoe axillaris*, *Alnus serrulata*, and *Aster prenanthoides* (Newell 1997).

Five fires have burned in and around Linville Gorge Wilderness Area over the past 15 years (Table 1). The Brushy Ridge wildfire occurred in 2000; it impacted approximately 4,000 hectares in and around Linville Gorge. Field observations across the burned area noted that fire severity was heterogeneous with high severity crown fires having occurred along ridges and low severity fires having burned mid-slopes as well as coves (Wimberly & Reilly 2007). Spring 2007

Table 1: Fires occurring in Linville Gorge Wilderness and surrounding area. The "Burned Area" column was calculated using burned area perimeters provided by the U.S. Forest Service (unpublished data).

Fire Name	Fire Ignition Date	Burned Area (hectares)
Brushy Ridge	October, 28 2000	4030.46
Pinnacle	30-Apr-07	954.11
Shortoff	29-Jun-07	1826.84
Sunrise	18-Apr-08	771.18
Table Rock	12-Nov-13	1043.23

witnessed two separate fires—the Pinnacle and Shortoff fires—that burned a large portion of the landscape previously burned in 2000, as well as some of the remaining unburned area surrounding Linville Gorge. The Sunrise wildfire occurred in 2008; it burned forest in McDowell County immediately adjacent to the Wilderness boundary (Waldrop et al. 2013). Most recently, a campfire spread in fall 2013 from Table Rock Mountain, and torched a portion of the area that had flamed in 2000 in addition to some previously unburned areas (USFS, unpublished data).

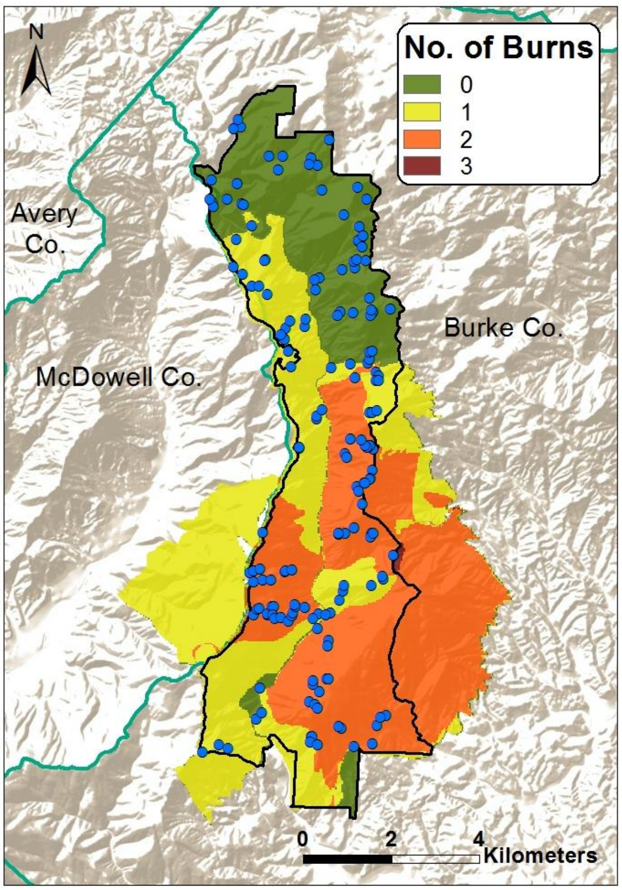

Figure 2: Locations of 1992 vegetation sample plots (in blue) with burn histories.

Historical Work

My Master's Project is a continuation of several historical studies. In 1992, a set of 181 permanent sample plots was established to describe vegetation communities in Linville Gorge Wilderness Area (Figure 2) (Newell 1997; Newell & Peet 1998). Plot locations were selected to be representative of geologic and topographic variation, and were sampled with the North Carolina Vegetation Survey (NCVS) protocol (Peet et al. 1998). Vegetation data has been retained for 176 of the 1992 plots. A subsequent study followed in 2003 that remeasured 25 of the 1992 plots. It was intended to capture the effects of the 2000 wildfire, and to help inform management decisions for rare species (Waldrop et al. 2013). Researchers used a similar methodology as the 1992 survey, including NCVS for vegetation data. Additionally, from 2009 to 2011, 154 of the 1992 plots were found and resurveyed to assess the 2007 and 2008 fires (Waldrop et al. 2013). Over the summer, our research team resampled 21 plots that burned in the 2013 Table Rock fire using the Waldrop et al. (2013) methodology. Cumulatively, remeasurement efforts have sampled plots that have burned in zero, one, and two fires (Figure 2; Table 2).

Table 2: Burn histories by community type for vegetation plots established in 1992 within Linville Gorge Wilderness Area, North Carolina. Plot establishment followed the design of the North Carolina Vegetation Survey (Peet et al. 1998).

All Plots												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
176	51	1992, 2003, 2010, 2011	34	1992, 2003, 2009, 2010, 2011	6	1992, 2003, 2009, 2010	10	1992, 2010, 2011, 2014	46	1992, 2003, 2009, 2010, 2011	27	1992, 2003, 2010, 2011, 2014
Xeric Evergreen Forests												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
84	22	1992, 2003, 2010, 2011	11	1992, 2003, 2009, 2010, 2011	5	1992, 2003, 2009, 2010	0	0	33	1992, 2003, 2009, 2010, 2011	13	1992, 2003, 2010, 2011, 2014
Acid Cove and Slope Forests												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
50	17	1992, 2003, 2010, 2011	11	1992, 2003, 2009, 2010, 2011	1	1992, 2010	10	1992, 2010, 2011, 2014	8	1992, 2003, 2009, 2010, 2011	3	1992, 2011, 2014
Montane Oak Forests												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
17	0	0	8	1992, 2009, 2010, 2011	0	0	0	0	3	1992, 2010, 2011	6	1992, 2011, 2014
Rock Outcrops												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
11	3	1992, 2011	0	0	0	0	0	0	1	1992, 2011	1	1992, 2011, 2014
Rich Cove and Slope Forests												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
9	5	1992, 2010, 2011	3	1992, 2010, 2011	0	0	0	0	1	1992	0	0
Alluvial Wetlands												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
3	2	1992, 2011	1	1992, 2010	0	0	0	0	0	0	0	0
Rocky Streamside Shrublands												
Total	**Un-burned**	**Sample Years**	**Burn 2000**	**Sample Years**	**Burn 2007**	**Sample Years**	**Burn 2013**	**Sample Years**	**Burn 2000 & 2007**	**Sample Years**	**Burn 2000 & 2013**	**Sample Years**
2	2	1992	0	0	0	0	0	0	0	0	0	0

METHODS

Data Collection

Vegetation Data

Plots that have been established with the NCVS methodology in Linville Gorge are comprised of a series of 100 square meter modules; the basic plot design consists of ten modules, with four interior modules chosen for intensive sampling of the herbaceous layer (Figure 3).

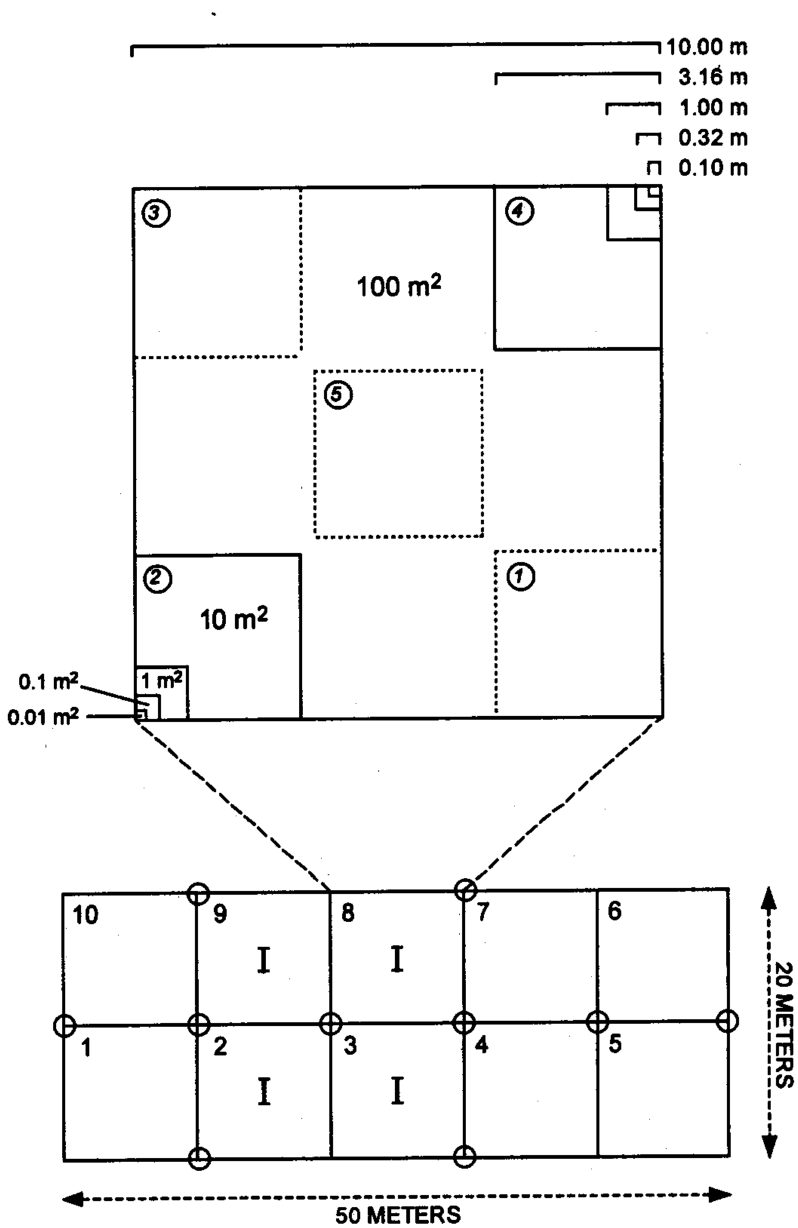

Figure 3: From Peet et al. 1998, North Carolina Vegetation Survey basic plot structure. Modules marked with "I" indicate modules that undergo intensive sampling.

However, in certain cases due to the size of the target community, fewer modules have been installed. The most intensive sampling level, which was implemented by Newell (1997), requires that, within each intensive module, subsampling of the herbaceous layer will occur in two corners. Overstory should be sampled in all modules (Peet et al. 1998). The study in 2003 did not sample intensively; rather, only overstory data was collected at each of the one, two, or four designated intensive modules, depending on plot size.

Waldrop et al. (2013) implemented intensive sampling techniques, and followed the 2003 overstory data collection protocol (i.e. data was collected only on modules that were intensively sampled in 1992). All living trees, shrubs, and woody vines above breast height (1.4 meters) were taxonomically classified, measured, and tallied into one of the following size ranges: 0-1 cm, 1-2.5 cm, 2.5-5 cm, 5-10 cm, 10-15 cm, 15-20 cm, 20-25 cm, 25-30 cm, 30-35 cm, 35-40 cm, and >40 cm (Figure 4 is a sample datasheet from our 2013 study). For any woody stem greater than 40 cm in diameter, the exact DBH was recorded. Whether the specimen was alive or dead at the time of sampling also was documented for all efforts subsequent to the 1992 study.[1] Diameters were measured at DBH and on the upslope side, if applicable. Multiple stems arising from a common root system were measured individually if they branched below 0.5 meters above ground level. Stems that branched above 0.5 meters but below 1.4 meters were measured at the narrowest point below the branch.

Linville Gorge Wilderness Area Natural Woody Stem Data

Leader: Team: Plot #: Date: Plot Size: x Page___of___

			Inches	0-0.39"		0.39-0.98"		0.98"		1.97"		3.94"		5.91"		7.87"		9.84"		11.81"		13.78"		15.75"	
				SAPLINGS--DBH (cm)				Tree--DBH (cm)																	
Code	Sp?	Species	Live/ Dead	0-1		1-2.5		2.5-		5-		10-		15-		20-		25-		30-		35-		>= 40	
				L	D	L	D	L	D	L	D	L	D	L	D	L	D	L	D	L	D	L	D	L	D

Figure 4: Sampling datasheet used in 2014. Adopted from Waldrop et al. 2014 (unpublished report) sampling methodology and NCVS (Peet et al. 1998).

[1] NCVS does not sample dead individuals.

Geospatial Data

Environmental Variables

Elevation, slope, geology and soil types, and site moisture all contribute to the geographic restriction of vegetation community types in Linville Gorge Wilderness Area (Newell 1997). To capture these sources of variation in the Linville vegetation data, corresponding geospatial datasets were downloaded and/or calculated. Vegetation classifications (Newell 1997) also were included to capture environmental variables important to plant community distribution that were omitted from analysis.

A Digital Elevation Model (DEM) (Figure 5) for North Carolina was acquired as a raster dataset with three-meter resolution from USGS National Mapping Service. From the DEM, ten other environmental variables were computed: Aspect, Curvature, Euclidean Distance to Streams, Flow Length, Insolation, Slope, Slope Position, Topographic Convergence Index (TCI), and Topographic Position Index (TPI) (see Data Processing, Environmental Variables).

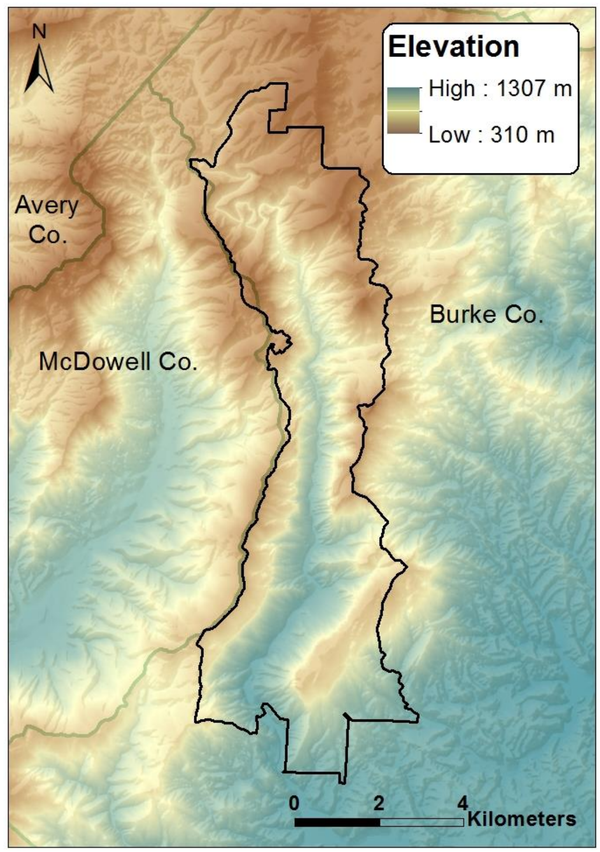

Figure 5: Digital Elevation Model for Linville Gorge Wilderness Area

Additionally, soil classifications for North Carolina were obtained as polygons from the U.S. Department of Agriculture's Natural Resources Conservation Service (NRCS) Gridded Soil Survey Geographic (gSSURGO) Database. Geological classifications for North Carolina also were acquired as polygons from NRCS's National Design, Construction, and Soil Mechanics Center. Both of these datasets were digitized from 7.5-minute topographic quadrangles (SSURGO 2013) and were converted to 30 meter resolution rasters.

All environmental variable processing and extraction to plot point locations (USFS, unpublished data) was done in ArcGIS 10.2.2 (ESRI 2014) (Model 1a-c, Model 4 in Appendix B) using the North American Datum of 1983, Universal Transverse Mercator Zone 17 North (NAD 1983 UTM Zone 17N).

Fire Severity Variables

With respect to fire severity estimation, the domestic remote sensing community has focused largely on burn analysis in forests of the western U.S.; studies have established a strong correlation between field-estimated fire severity and the Normalized Burn Ratio (NBR) (e.g. Thompson et al. 2007, Miller et al. 2009). For two Linville Gorge fires, Wimberley and Reilly (2007), as well as Waldrop et al. (2013), have found significant correlations between Composite Burn Indices (CBI) calculated with field data and change in Differenced Normalized Burn Ratio (dNBR) values computed with Landsat images. Given these results, dNBR was selected as a metric for burn severity.

Before- and after-fire Landsat image selection was timed for the growing season prior to and following the fire (Table 3). Preference was given to images that fell in the relatively constant photosynthetic period of the growing season. Five images were obtained from Landsat 5 Thematic Mapper (TM) Climate Data Record (CDR), pre-corrected to land surface reflectance as well as for geometric and terrain precision (USGS). For the 2013 Table Rock fire, two Landsat 8 Operational Land Manager (OLI) images, corrected only for geometric precision, were selected. Each image had a resolution of 30 meters and was free of clouds for the fire event area of interest. Unpublished U.S. Forest Service data provided perimeters for the Linville Gorge Wilderness Area as well as each of the fires.

Table 3: Landsat image data used in fire severity calculations.

Fire Name	Satellite	Before Image Date	Path, Row	After Image Date	Path, Row
Brushy Ridge	Landsat 5 TM	11-Jun-00	18, 35	5-Jun-01	17, 35
Pinnacle	Landsat 5 TM	10-Jun-06	18, 35	16-Aug-07	18, 35
Shortoff	Landsat 5 TM	10-Jun-06	18, 35	16-Aug-07	18, 35
Sunrise	Landsat 5 TM	16-Aug-07	18, 35	25-Jun-08	17, 35
Table Rock	Landsat 8 OLI	13-Jun-13	18, 35	24-May-14	17, 35

Image selection and pre-processing (i.e. radiometric and atmospheric correction) was performed in ENVI version 5.1 (Exelis Visual Information Solutions 2013). Processing steps, including the production of dNBR images and extraction to plot point locations (USFS, unpublished data), was done in ArcGIS 10.2.2 (ESRI 2014) (Model 2a-b, Model 3a-c, Model 4 in Appendix B).

Data Processing

Vegetation Data

Basal Area and Density Calculations

Data was first cleaned of entry errors or discrepancies in coding systems. This required the merging of counts with separate codes for the same species (e.g. *Castanea dentata* as CASTDEN and CASTDNT) and the removal of typing errors. From the species dataset, rare tree species that occurred on five or fewer plots were removed, and only plots with overstory data were included. Unless otherwise noted, this and all subsequent processing steps were done in Microsoft Excel (Microsoft Office 2014). Sixty-six species were included in analysis; all included species are listed in in Appendix Table A.1. Species will be referenced by their code within subsequent figures.

As described above, the raw species datasets include per-module counts of woody-stemmed species broken into diameter at breast height (DBH) size classes: 0-1 cm, 1-2.5 cm, 2.5-5 cm, 5-10 cm, 10-15 cm, 15-20 cm, 20-25 cm, 25-30 cm, 30-35 cm, 35-40 cm, and >40 cm. Live and dead individuals of the same species were recorded separately, and have been treated separately in this analysis (e.g. ACERRUB_L and ACERRUB_D). Including dead individuals, 105 live-dead combinations were incorporated. Counts of each unique species/condition combination were aggregated to the plot level within each size class, with the individual DBHs for trees over 40 cm in diameter being preserved using ArcGIS 10.2.2 (ESRI 2014). Then, basal area (BA) was calculated with the midpoint of each size class using Formula 1, which converts DBH recorded in centimeters to basal area in square meters.

$$(1) \qquad BA\ (m^2) = (\pi * (DBH/2)^2) / 10{,}000$$

The results then were changed into square meters per hectare for each size class and scaled by 100:

$$(2) \qquad BA\ (m^2/ha) = ((BA\ (m^2)) / (\text{number of modules in plot})) * 100$$

Density also was transformed to number of individuals per hectare and scaled by 100:

$$(3) \qquad \text{Density}\ (\#/ha) = ((\#\text{ of individuals}) / (\text{number of modules in plot})) * 100$$

These values were aggregated across size classes to totals per species per plot for each sampling year, and relativized by sample unit totals (i.e. where the samples are rows and the species are columns).

Importance Values

Previous multivariate statistical analysis of Linville vegetation community changes with fire explored only abundance data for species (Waldrop et al. 2013). Accordingly, results were biased by species that tended to occur in high numbers on suitable sites (e.g. *Acer rubrum, Nyssa sylvatica,* and *Kalmia latifolia*). Though the tradeoff can be more opaque interpretation, Importance Values (IVs) can mediate the effects of large tree size and high numbers of small trees on the analysis results (McCune & Grace 2002). IVs are the sum (or average) of vegetation information such as relative basal area, relative density, and relative frequency. Because these events are concerns in the Linville dataset, IVs were selected to represent species information. Relative basal area and relative density were totaled to form Importance Values for each species on each plot. The Importance Values ranged from zero to 200.

Data also was subset to each of the seven community types by burn history, and for all plots by sampling year and burn history (Table 2). Packages “reshape” (Wickham 2007) and “matrix”

(Bates & Maechler 2015) were used in R v. 3.1.2 (R Development Core Team 2013) to facilitate these steps.

Geospatial Data

Environmental Variables

Six environmental variables were correlated with vegetation data (Table 4): Aspect, Elevation, Slope, Slope Position, Topographic Convergence Index (TCI), and Topographic Convergence Index (TPI). These data were calculated from the USGS DEM in ArcGIS 10.2.2 (ESRI 2014).

From 0° to 360° (due north to due north), aspect is the direction that a slope faces (ESRI 2012). Elevation, as derived from the USGS DEM, is the height above sea level, in meters (USGS 2015). Slope is the maximum rate of change in elevation value from a cell compared to its neighbors in a three-by-three processing neighborhood (ESRI 2012). TPI "compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell" (Weiss 2007). In this analysis, an inner radius of one cell and an outer radius of five cells were specified. Slope Position is the classification of TPI values based on standard deviations away from the mean TPI value. Finally, Topographic Convergence Index, also called the Topographic Wetness Index, is a quantification of upslope area and slope effects on hydrology (Sorensen et al. 2006).

Table 4: Environmental variables included in statistical analyses of Linville Gorge Wilderness Area vegetation data.

Variable	Spatial Resolution (meters)	Description	Calculation	Description/Calculation Source	Primary Data Source	Data Download Source
Vegetation Community Classification	NA	Sample plot's vegetation community type.	Based on Carolina Vegetation Survey results.	Newell 1997	Newell 1997	NA
Geology	30	Geology type.	Compiled from previous studies.	USDA NRCS	USDA NRCS	nrcs.usda.gov
Soil	30	Soil type.	Compiled from previous studies.	USDA NRCS		
Aspect	3	Direction that a slope faces.	Counterclockwise in degrees from 0 to 360 (due north to due north).	ArcGIS Resource Center	USGS National Mapping Services	national map.gov
Elevation	3	Height above sea level, in meters.	Designated by Digital Elevation Model for NC.	USGS National Mapping Services		
Slope	3	Steepness of terrain, in degrees.	$\tan\left(\sqrt{([dz/dx]^2 + [dz/dy]^2)}\right) * 180/\pi$	ArcGIS Resource Center		
Slope Position	3	Geographic location of a slope on a hillside, as computed from the Topographic Position Index.	Threshold TPI by +/- 3 std. dev. from mean TPI value.	Weiss 2007		
Topographic Convergence Index (TCI)	30	Quantification of topographic control (i.e. upslope area and slope) on hydrological processes.	$\ln(\textit{upslope area}/\tan(\textit{slope}))$	Sorensen et al. 2006		
Topographic Position Index (TPI)	30	TPI "compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell."	DEM - Focal Mean of DEM + 0.5	Weiss 2007		

Fire Severity Variables

Each pair of before- and after-fire Landsat images (Table 3) was inspected for geometric precision; all sets were determined to be geometrically correct and topographically aligned. Landsat 5 TM CDR images were not pre-processed, as they were downloaded in units of surface reflectance. The two Landsat 8 OLI images were corrected radiometrically, and then atmospherically with Dark Object Subtraction using a visually selected Region of Interest. Negative reflectance values, generated from the Dark Object Subtraction, were converted to zero. Next, for the Landsat 5 images, Normalized Burn Ratios were calculated with Formula (4), and for Landsat 8 images, NBR was computed with Formula (5):

$$\text{(4)} \qquad \text{NBR} = (\text{Band 4} - \text{Band 7}) / (\text{Band 4} + \text{Band 7})$$

$$\text{(5)} \qquad \text{NBR} = (\text{Band 5} - \text{Band 7}) / (\text{Band 5} + \text{Band 7})$$

With the before- and after-fire NBR images, change in NBR was calculated and rescaled using Formula (6):

$$\text{(6)} \qquad \text{dNBR} = 1{,}000 * (\text{NBRpre} - \text{NBRpost})$$

Results were subset to the areas specified by the Forest Service fire perimeters (unpublished data) and summary statistics were computed for the images. Burn frequency and severity variables were computed from the information extracted to the vegetation plots (Table 5).

Table 5: Fire severity variables included in statistical analysis of Linville Gorge Wilderness Area vegetation data.

Fire Severity Variable	Description
Brushy Ridge Fire Severity	Severity of Brushy Ridge fire as quantified by the Differenced Normalized Burn Ratio (dNBR).
Burned in 2000	Binary variable indicating whether a sample plot burned in 2000.
Burned in 2007	Binary variable indicating whether a sample plot burned in 2007.
Burned in 2013	Binary variable indicating whether a sample plot burned in 2013.
Cumulative Fire Severity	Sum of dNBR values for each fire.
Pinnacle Fire Severity	Severity of Pinnacle fire as quantified by dNBR.
Shortoff Fire Severity	Severity of Shortoff fire as quantified by dNBR.
Table Rock Fire Severity	Severity of Table Rock fire as quantified by dNBR.
Total Number of Burns	Number of times (0, 1, or 2) times a sample plot has burned since 2000.

Excluded Variables

Several other environmental variables were calculated from the DEM, but were excluded from analyses due to lack of correlation with the vegetation data. These were Insolation, Landform, Euclidean Distance to Streams, Flow Length, and Curvature. Insolation is a measure of solar radiation on Earth's surface; it was computed for an azimuth of 225 degrees and an altitude of 30 degrees (ESRI 2012). Landform classifies the combination of small- (e.g. an inner radius of one cell and an outer radius of five cells) and large-scale (e.g. an inner radius of 20 cells and an outer radius of 25 cells) TPI into landform categories such as open slopes and high ridges (Weiss 2007). Euclidean Distance to Streams is the straight-line distance (in meters) to the nearest stream. Streams were specified from the DEM as series of cells that had more than 400 cells contributing flow. Flow Length is the distance (in meters) that water travels to the nearest DEM-derived stream. Finally, Curvature is a quantification of the amount of curvature in a DEM surface, as calculated, on a cell-by-cell basis, by the second derivative value of the DEM (ESRI 2012).

Additionally, the fire severity variables for the Sunrise fire (i.e. Burned in 2008, Sunrise Fire Severity) were removed because none of the Newell plots were burned in that fire.

Vegetation Composition and Structure Analyses

Nonmetric multidimensional scaling (NMS) is an ordination technique that aims to place samples into a compressed ordination space while preserving ecological distances in rank order. The goal is to compress highly dimensional data into fewer dimensions that capture main sources of variation. It is an iterative process in which the practitioner specifies the dimensionality of the data (Legendre & Legendre 2012).

The following analysis applied NMS to the Linville Gorge dataset. An extended Bray-Curtis index was computed for overstory species dissimilarity among the samples. Dimensionality in the data was explored with a step-down procedure, starting with six axes and proceeding to one. At this step, sixty ordinations were performed using random start configurations with ten replicate ordinations for each axis. An examination of the scree plots of the stress and R^2 values from the step-down procedure provided evidence of five-dimensionality in the data.

Then, an NMS ordination was performed for five dimensions with 100 replicate runs for each dimension; again, the random start configuration was used. The iteration with the least amount of stress was identified and rotated with Principal Components Analysis (PCA) to force the most variation on Axis 1, the second most on Axis 2, etc. for each subsequent axis. For the final NMS ordination, a Shepard diagram of the extended Bray-Curtis dissimilarities was produced, and the R^2 values for each axis were calculated. Axis 2 had to be calculated from the total variation accounted rather than from Axis 1, as Axis 2 was not fit to the residuals of Axis 1. The same process was followed with Axes 3, 4, and 5. Weighted averaging was implemented to produce the species correlation scores with the NMS axes. Next, environmental variables were correlated with the five NMS axes. These materials were used to produce joint biplots with correlation vectors for environmental variables most correlated with NMS Axes 1 and 2. Change vectors connecting vegetation plots through time (i.e. at each sample year) were added to the NMS ordination. This step facilitated the visualization of structural and compositional changes.

The NMS ordination procedure was completed in R v. 3.1.2 (R Development Core Team 2013) with the “ecodist” contributed package (Goslee & Urban 2010). Extended Bray-Curtis dissimilarities and weighted averages for species scores were calculated with the “vegan” contributed package (Oksanen et al. 2013).

Restoration Goals Analyses

Ericaceous species recorded in the vegetation data were *Kalmia latifolia, Rhododendron catawbiense, Rhododendron maximum, Rhododendron minus, Rhododendron periclymenoides, Vaccinum corymbosum, Vaccinum pallidum, Vaccinium simulatum,* and *Vaccinium stamineum*; all of these species were incorporated in the analysis. Fire intolerant species of interest to TWS were *Acer rubrum, Oxydendrum arboreum,* and *Pinus strobus*. Fire dependent species selected included *Pinus pungens, Pinus rigida, Quercus alba, Quercus coccinea, Quercus montana (syn. Quercus prinus)*, and *Quercus rubra*. Finally, *Paulownia tomentosa* was the single nonnative, invasive species of concern; only it was analyzed in the invasive species tests. For each set of species, data was subset to exclude all but those of interest. Afterward, burn histories were isolated for each sampling period. The 2009 to 2011 samples were aggregated to increase sample sizes (Table 6).

Table 6: Burn history for plots by sample year.

		Measurement Year			
		1992	2003	2009-11	2014
Burn History	Unburned	51	3	44	0
	Burned 1x: 2000	34	9	32	0
	Burned 1x: 2007	6	1	6	0
	Burned 1x: 2013	10	0	10	10
	Burned 2x: 2000, 2007	46	11	42	0
	Burned 2x: 2000, 2013	27	1	17	11

One-sided paired t-tests were run to test the effect of fire events on the mean Importance Values for live ericaceous, fire intolerant, fire dependent, and invasive species subsets (Table 7). Though t-tests assume parametric data and the Linville vegetation data is not

Table 7: Mean Importance Values for species of interest by sample year and burn history.

Sample year	Un-burned	Burned 2000	Burned 2007	Burned 2013	Burned 2000 & 2007	Burned 2000 & 2013
Ericaceous Species						
1992	59.8	56.3	43.5	57.3	57.0	62.0
2003	74.2	18.7	71.9	NA	36.9	4.8
2009-11	63.3	17.3	10.3	52.5	4.8	31.1
2014	NA	NA	NA	40.0	NA	12.3
Fire Intolerant Species						
1992	6.8	6.9	5.8	5.5	7.3	3.1
2003	17.6	16.7	18.7	NA	15.6	3.2
2009-11	6.8	16.8	10.3	10.5	19.5	7.1
2014	NA	NA	NA	10.9	NA	12.2
Fire Dependent Species						
1992	27.3	35.1	46.9	4.5	39.5	39.0
2003	47.0	33.8	21.3	NA	45.7	4.0
2009-11	17.7	19.4	16.4	2.0	7.2	29.0
2014	NA	NA	NA	2.3	NA	10.0
Invasive Species						
1992	0.0	0.0	0.0	0.0	0.0	0.0
2003	0.0	20.0	0.0	NA	0.0	0.0
2009-11	0.0	1.5	0.2	0.0	9.7	0.2
2014	NA	NA	NA	0.0	NA	0.0

normally distributed, t-tests should be relatively robust to variations from normality (Gotelli & Ellison 2013). For both ericaceous and fire intolerant species, the hypothesis tested was that mean IVs were lower after fires than before fires. Hypotheses for fire dependent and invasive species were that mean IVs increased after fire events. The alternative hypothesis for all t-tests was that no significant difference existed between mean IVs before and after fire. These comparisons occurred between unburned and once burned, unburned and twice burned, and once burned and twice burned samples.

Data Limitations

Vegetation Data

There are several limitations and assumptions associated with the Linville vegetation dataset. Because of the numerous sampling efforts, inconsistencies in species identification accuracy are likely to have occurred. Importance Values for each species have been chosen as a structural and compositional representation of Linville's forests. Direct interpretation of these values—i.e. whether an increase in importance is due to more abundant small stems, or to larger trees increasing from one size class to the next—is not possible. Additionally, due to low sample sizes for sample year by burn history within each community type, Objective 2 analyses have been done for all plots. However, it would have been ideal to perform the analyses by community type. Also for Objective 2, another statistical technique that does not assume normally distributed data could be explored, with the potential tradeoff of less interpretable results. A final consideration is that, for management decision implications, it has been assumed that the vegetation plot samples are representative of the larger Linville Gorge Wilderness Area forests.

Geospatial Data

Other considerations pertain to the geospatial variables that have been selected for analyses. First, they are assumed to be representative of conditions on each plot. Verifying or supplementing these data with field comparisons would provide additional information about site environments. Next, best available Landsat images have been chosen for analysis. However, particularly for the 2007 and 2008 fires, persistent cloud cover has necessitated the selection of images that do not align precisely on anniversary dates. For fires occurring in early spring (i.e. Pinnacle, Shortoff, and Sunrise), before-fire images have been designated for the growing season of the previous year. This will have introduced error in the estimation, as the analysis could not control for factors impacting vegetation condition in the intervening year. Lastly, while previous research has established a high correlation of dNBR with a Composite Burn Index (Wimberley & Reilly 2007), alternative standardized fire severity quantification methods (e.g. RdNBR) or a site-specific index should be explored for increased levels of accuracy.

Results

Vegetation Composition and Structure

Fire Severity Patterns

Table 8: dNBR summary statistics for wildfires occurring in and around Linville Gorge Wilderness Area between 2000 and 2013.

Fire Name	Year	Mean	Min.	Max.	Std. Dev.
Brushy Ridge	2000	149.70	-178.00	1036.00	139.17
Pinnacle	2007	195.16	-398.00	782.00	265.57
Shortoff	2007	180.33	-219.00	912.00	298.16
Sunrise	2008	216.55	-48.00	1076.00	287.58
Table Rock	2013	132.82	-1363.00	1107.00	216.37

Fire severity patterns were discernable with the dNBR images (Appendix Figures C.1-C.5). Regions that experienced vegetation regrowth, rather than charring, were characterized with negative values; areas with burned vegetation received positive values. Higher positive values provided evidence for increasing fire severity. A typical range for a scaled dNBR is from -500 to 1,300 (+/- 100). Values less than or exceeding that range are likely to be anomalies in the data (USFS 2014). Ridges and hilltops experienced highest levels of severity; hillsides typically burned with moderate to low severity, and land adjacent to the river remained unburned.

All fires had a mean severity less than 220.00 (Table 8). The Brushy Ridge fire was low severity, with the majority of pixel values remaining below 125.00. Occurring next, Pinnacle Fire burned more severely than all but Sunrise Fire, with a mean index value of 195.16; low severity pixel values were most prevalent. Shortoff Fire had a mean severity of 180.33, and burned relatively uniformly in the moderate severity range. Sunrise was most severe with a mean value of 216.55. However, burning was less uniform with smaller patches of high severity fire along ridges while the remainder of the area was unburned or burned with low severity. Table Rock was the least severe fire with a mean value of 132.82; the majority of the area was unburned or burned with low severity.

Description of Vegetation and Environmental Data

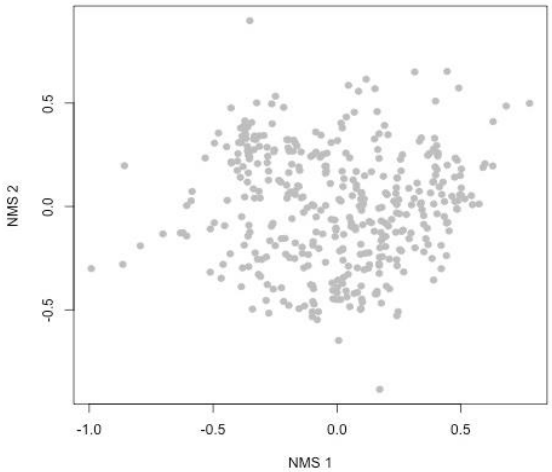

Figure 6: NMS ordination plot of Linville Gorge vegetation samples (1992-2014). Samples are represented in grey.

A five-axis solution for the Linville Gorge vegetation dataset had a minimum stress of 0.153, with a Mantel's correlation of 0.858 (p=0.001). In an ordination graph, empty space is significant in that it represents ecological dissimilarity of samples. As evidenced by the wide distribution of the data samples within the NMS space of Axes 1 and 2, vegetation in Linville Gorge was highly heterogeneous (Figure 6). NMS Axis 1 captured the largest amount of variation (26.0 percent) in the dataset (Table 9). It was most highly correlated with the environmental variables of Slope Position and Slope (degrees) as well as Table Rock Fire Severity and Cumulative Fire Severity. The species with weighted averages that loaded most heavily on NMS Axis 1 were live *Carya glabra* (CARYGLA_L), *Fagus grandifolia* (FAGUGRA_L), *Amelanchier laevis* (AMELLAE_L), and *Pinus rigida* (PINURIG_L) (Table 10). NMS Axis 2 accounted for 21.8 percent of the variation in the dataset. It was most highly correlated with Geology and Elevation on one end, and with the Total Number of Burns as well as fire variables for the 2000 and 2007 fires on the other. The species most heavily loaded on this axis were live *Paulownia tomentosa* (PAULTOM_L), *Betula alleghaniensis* (BETUALL_L), *Ilex montana* (ILEXMON_L), and dead *Fothergilla major* (FOTHMAJ_D).

Table 9: Axes statistics and environmental variable correlations with NMS Axes for the Linville Gorge Wilderness Area vegetation dataset. TCI is the Topographic Convergence Index, and TPI is the Topographic Convergence Index.

	NMS Axes				
	Axis 1	**Axis 2**	**Axis 3**	**Axis 4**	**Axis 5**
R^2	0.232	0.209	-0.135	-0.572	-1.110
Total R^2	0.232	0.441	0.538	0.639	0.736
Proportion of Variance	0.260	0.218	0.182	0.175	0.165
Mean Stress	0.624	0.343	0.241	0.187	0.153
	Environmental Variable Correlations				
Aspect		-0.090			
Brushy Ridge Fire Severity		0.189	-0.146		
Burned in 2000		0.340	-0.252		
Burned in 2007		0.305	-0.154	-0.155	
Burned in 2013	-0.113				
Cumulative Fire Severity	-0.099	0.247	-0.213	-0.085	
Elevation		-0.167			
Geology		-0.264	0.14		
Pinnacle Fire Severity		0.309	-0.099		
Shortoff Fire Severity				-0.162	-0.110
Slope (degress)	0.102			0.090	-0.098
Slope Position	0.144				
Soil		-0.108			
Table Rock Fire Severity	-0.142		-0.166		
Topographic Convergence Index					0.142
Total Number of Burns		0.352	-0.255	-0.091	
Topographic Position Index	-0.084				
Vegetation Class		0.130	-0.136		

The relationships between the environmental variables and the live species most correlated with each of the first two axes are highlighted in the biplots in Figure 7. Elements most highly correlated with NMS Axis 1 are on the left and those with NMS Axis 2 are on the right. *Amelanchier laevis* and *Pinus rigida* both correlated most strongly on the end of the axis with greatest loading of Slope and Slope Position (represented as “SlopePosition”). At the other end of the axis, *Fagus grandifolia* and *Carya glabra* were sorting along a gradient of cumulative fire severity, as well as the Table Rock fire severity (labeled as “TotalSeverity”). *Betula alleghaniensis* and *Ilex montana* had the strongest relationship with the portion of NMS Axis 2 that shared its highest correlation with Elevation and Geology (both coded as “Elevation”). *Pyrularia pubera* (PYRUPUB_L) and *Paulownia tomentosa* were most highly correlated with the 2000 and 2007 severity variables, as well as the total number of burns on a plot (all represented as “TotalBurns”).

Table 10: Correlations (r) for species with NMS axes. Species codes explained in Table 4 in Appendix A.

Species	Axis 1	Species	Axis 2	Species	Axis 3	Species	Axis 4	Species	Axis 5
CARYGLA_L	-0.586	PAULTOM_L	-0.580	FRAXAME_L	-0.397	ILEXMON_L	-0.366	RHUSCOP_L	-0.406
FAGUGRA_L	-0.489	FOTHMAJ_D	-0.433	RHODPER_L	-0.274	VITIAES_D	-0.351	ARALSPI_L	-0.402
VITIAES_D	-0.476	PINUSPP_D	-0.390	CORNFLO_L	-0.245	RUBUSPP_L	-0.321	PAULTOM_D	-0.352
CARYALB_L	-0.467	PYRUPUB_L	-0.388	QUERALB_L	-0.221	ACERPEN_L	-0.304	CASTDEN_D	-0.290
LIRITUL_L	-0.437	QUERCOC_D	-0.383	PYRUPUB_L	-0.220	PARTQUI_L	-0.268	PAULTOM_L	-0.240
PINUVIR_L	0.387	RHODMAX_L	0.276	PINUSPP_D	0.381	QUERMON_L	0.234	QUERALB_L	0.277
PINUPUN_L	0.396	TSUGCAR_L	0.303	FOTHMAJ_D	0.382	TSUGCAN_L	0.260	RUBUSPP_L	0.297
VACCSTA_L	0.448	RHODMIN_L	0.315	ROBIHIS_L	0.399	ILEXOPA_L	0.371	PRUNPEN_L	0.316
PINURIG_L	0.449	ILEXMON_L	0.548	RHODMIN_D	0.405	PAULTOM_L	0.433	QUERMON_L	0.317
AMELLAE_L	0.459	BETUALL_L	0.613	LEUCFON_L	0.407	FAGUGRA_L	0.474	RHODPER_L	0.327

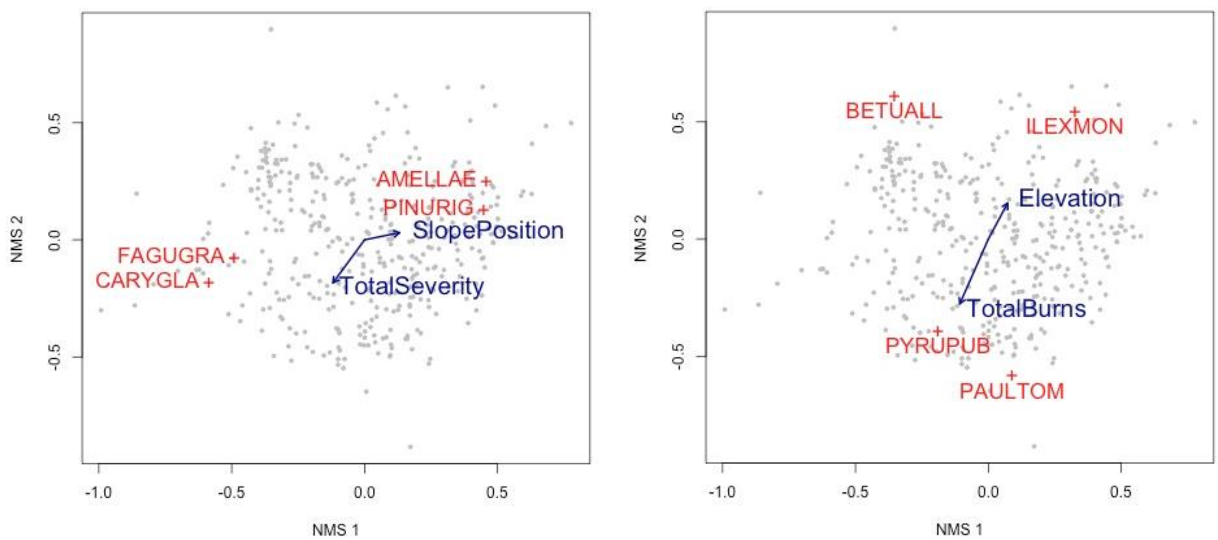

Figure 7: Biplots of NMS ordination with Linville Gorge samples. Samples are colored in grey. Live species with weighted averages that load most heavily on each axis are plotted and labeled in red. Environmental variable correlation vectors are labeled and displayed with blue arrows. Length of the arrow corresponds to the magnitude of the correlation, and direction displays the direction of correlation of the environmental variable with the NMS axis. Variables most correlated with NMS Axis 1 are on the left and with NMS Axis 2 are on the right. "SlopePosition" represents both Slope (degrees) and Slope Position. "TotalSeverity" indicates both the cumulative fire severity and the Table Rock Fire severity. "Elevation" is intended to represent both Elevation and Geology, and "TotalBurns" is Total Number of Burns as well as fire variables for the 2000 and 2007 fires. Species codes explained in Appendix Table A.1.

In addition to Geology, Total Number of Burns and Burned in 2000 were most correlated with NMS Axis 3, which accounted for 18.2 percent of the data variation. Weighted averages for live *Fraxinus americana* (FRAXAME_L), *Rhododendron periclymenoides* (RHODPER_L), and *Leucothoe fontanesiana* (LEUCFON_L), and dead *Rhododendron minus* (RHODMIN_D) loaded most heavily on this axis. *Rhododendron minus* and *Leucothoe fontanesiana* loaded on the axis end most correlated with Geology; the other species were most correlated with the fire variables. Containing 17.5 percent of the variation, NMS Axis 4 was most correlated with 2007 fire severity variables, as well as with Slope. Only one new species, dead *Vitis aestivalis* (VITIAES_D) was captured by this axis. Live *Paulownia tomentosa* and *Fagus grandifolia* loaded most heavily on the Slope end of the axis, while *Vitis aestivalis* and live *Ilex montana* correlated with the fire severity variables. Finally, Topographic Convergence Index (TCI) and Shortoff fire severity loaded most heavily on NMS Axis 5; this axis explained the final 16.5 percent of variation in the dataset. Species that correlated include live *Rhus copallinum* (RHUSCOP_L) and *Aralia spinosa* (ARALSPI_L) on the fire severity end, and *Quercus montana* (QUERMON_L) as well as *Rhododendron periclymenoides* (RHODPER_L) on the side of TCI.

Forest Change

Acid Cove and Slope as well as Xeric Evergreen Forests changed compositionally and structurally with fire along both NMS Axis 1 and Axis 2 (Figure 8). Burned plots moved generally down and right within the ordination, indicating shifts with increasing number of burns. Unburned plots did not exhibit a trend; rather, their movement varied randomly. All Montane Oak Forest samples burned either once or twice. Sample plots followed comparable change trajectories within the NMS space. Other community types had too few samples to reveal patterns of change with fire.

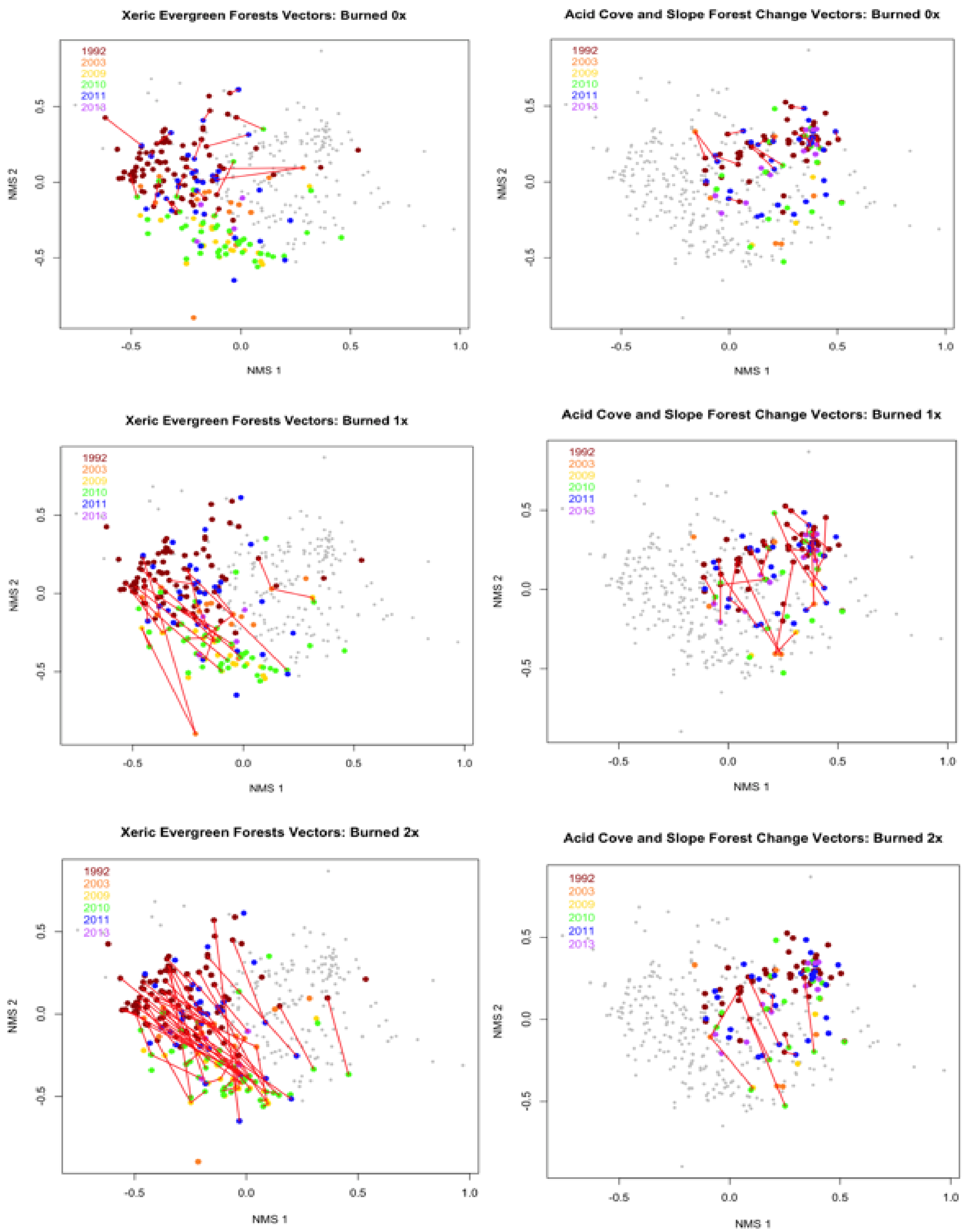

Figure 8: NMS ordination results for Xeric Evergreen (left) and Acid Cove and Slope Forests (right). Vegetation samples are denoted with warm-colored points for the early sample years to cool-colored points for the later sample years; all other plots are colored in grey. Red change vectors are connecting one plot through its sampling history. Results have been divided by burn history of zero, one, or two burns.

Restoration Goals

Ericaceous Species

Null hypotheses for live ericaceous species were rejected in favor of the alternatives. Across all sample plots, the mean importance value for ericaceous shrubs decreased significantly with each fire event (Table 11). IVs for ericaceous species were significantly reduced after one fire and two fires as compared to unburned plots, and plots burned twice also had lower IVs as compared to once burned plots. Unburned plots demonstrated no significant differences in mean IVs over time.

Table 11: One-sided paired t-test results for live ericaceous species across all Linville Gorge sample plots. Years labeled in green represent unburned plots while those in yellow are once-burned plots and those in red are twice-burned plots. Within each burn category, post-fire years are hypothesized to have lower mean IVs for ericaceous species than pre-fire years (X='Before' year, Y='After' year). For burn histories with multiple post-fire sample years, each post-fire year has been compared separately to the pre-fire year.

Ericaceous Species

Unburned		
Before: 1992		
After	**df**	**p-value**
2003	2	0.127
2009-11	43	0.845

Burned 2000		
Before: 1992		
After	**df**	**p-value**
*2003	20	<0.000
**2009-11	19	<0.000

* Includes all 2003 samples.

Burned 2007		
Before: 1992		
After	**df**	**p-value**
2009-11	5	0.014

Burned 2013		
Before: 1992		
After	**df**	**p-value**
2014	9	0.047
Before: 2009-11		
2014	9	0.008

** Includes all samples of the 2000 and 2013 fires.

Burned 2000 and 2007		
Before: 1992		
After	**df**	**p-value**
2003	10	0.007
2009-11	41	<0.000
Before: 2003		
2009-11	10	0.003

Burned 2000 and 2013		
Before: 1992		
After	**df**	**p-value**
2009-11	15	0.001
2014	9	<0.000
Before: 2009-11		
2014	10	<0.000

Fire Intolerant Species

The null hypotheses for live fire intolerant species were rejected. However, the alternative hypotheses were not proven: fire intolerant species significantly *increased* ($p<0.05$) in importance for each fire event history (Table 12). However, once-burned plots did not differ significantly from twice-burned, and plots that burned in 2013 were not significantly different after the fire event as compared to the 2009-11 sample period. Mean IVs of fire intolerant species on unburned plots did not change through time.

Table 12: One-sided paired t-test results for live fire intolerant species across all Linville Gorge sample plots. Years labeled in green represent unburned plots while those in yellow are once-burned plots and those in red are twice-burned plots. Within each burn category, post-fire years are hypothesized to have lower mean IVs for fire intolerant species than pre-fire years (X='Before' year, Y='After' year). Significant *increases* ($p<0.05$) in mean IV are marked in blue. For burn histories with multiple post-fire sample years, each post-fire year has been compared separately to the pre-fire year.

Fire Intolerant Species

Unburned		
Before: 1992		
After	**df**	**p-value**
2003	2	0.758
2009-11	43	0.242

Burned 2000		
Before: 1992		
After	**df**	**p-value**
*2003	20	0.999
**2009-11	19	1.000

* Includes all 2003 samples.

Burned 2007		
Before: 1992		
After	**df**	**p-value**
2009-11	5	0.957

Burned 2013		
Before: 1992		
After	**df**	**p-value**
2014	9	0.952
Before: 2009-11		
2014	9	0.586

** Includes all samples of the 2000 and 2013 fires.

Burned 2000 and 2007		
Before: 1992		
After	**df**	**p-value**
2003	10	0.996
2009-11	41	1.000
Before: 2003		
2009-11	10	0.925

Burned 2000 and 2013		
Before: 1992		
After	**df**	**p-value**
2009-11	15	0.997
2014	9	0.987
Before: 2009-11		
2014	10	0.935

Fire Dependent Species

Live fire dependent species did not increase in importance with fire events (Table 13). Rather, either the test failed to reject the null hypothesis—for both the 2007 and 2013 once-burned plots, and for earliest year comparisons from unburned to once-burned plots or once-burned to twice burned plots—or it was rejected due to a significant *decrease* in mean IVs. Unburned plots sampled in 2009-11 also exhibited significant decreases in fire dependent species.

Table 13: One-sided paired t-test results for live fire dependent species across all Linville Gorge sample plots. Years labeled in green represent unburned plots while those in yellow are once-burned plots and those in red are twice-burned plots. Within each burn category, post-fire years are hypothesized to have higher mean IVs for fire dependent species than pre-fire years (X='Before' year, Y='After' year). Significant *decreases* ($p<0.05$) in mean IV are marked in blue. For burn histories with multiple post-fire sample years, each post-fire year has been compared separately to the pre-fire year.

Fire Dependent Species

Unburned		
Before: 1992		
After	**df**	**p-value**
2003	2	0.238
2009-11	43	1.000

Burned 2000		
Before: 1992		
After	**df**	**p-value**
*2003	20	0.218
**2009-11	19	0.999

Burned 2007		
Before: 1992		
After	**df**	**p-value**
2009-11	5	0.982

Burned 2013		
Before: 1992		
After	**df**	**p-value**
2014	9	0.915
Before: 2009-11		
2014	9	0.146

Burned 2000 and 2007		
Before: 1992		
After	**df**	**p-value**
2003	10	0.201
2009-11	41	1.000
Before: 2003		
2009-11	10	0.999

Burned 2000 and 2013		
Before: 1992		
After	**df**	**p-value**
2009-11	15	0.943
2014	9	0.959
Before: 2009-11		
2014	10	0.946

* Includes all 2003 samples.

** Includes all samples of the 2000 and 2013 fires.

Invasive Species

Only the comparison between 1992 to 2009-11 samples that were burned twice in 2000 and 2007 exhibited a significant increase in *Paulownia tomentosa* (Table 14). For all other tests, the null was not rejected, often due to lack of species occurrences (e.g. Burned 2013). Documented species occurrences also were inadequate to draw conclusions about unburned plots.

Table 14: One-sided paired t-test results for live invasive species across all Linville Gorge sample plots. Years labeled in green represent unburned plots while those in yellow are once-burned plots and those in red are twice-burned plots. Within each burn category, post-fire years are hypothesized to have higher mean IVs for invasive species than pre-fire years (X='Before' year, Y='After' year). 'NA' signifies a lack of *Paulownia tomentosa* occurrences on the sample plots. For burn histories with multiple post-fire sample years, each post-fire year has been compared separately to the pre-fire year.

Invasive Species

Unburned		
Before: 1992		
After	**df**	**p-value**
2003	2	NA
2009-11	43	NA

Burned 2000		
Before: 1992		
After	**df**	**p-value**
*2003	20	0.165
**2009-11	19	0.119

* Includes all 2003 samples.

Burned 2007		
Before: 1992		
After	**df**	**p-value**
2009-11	5	0.182

Burned 2013		
Before: 1992		
After	**df**	**p-value**
2014	9	NA
Before: 2009-11		
2014	9	NA

** Includes all samples of the 2000 and 2013 fires.

Burned 2000 and 2007		
Before: 1992		
After	**df**	**p-value**
2003	10	NA
2009-11	41	0.017
Before: 2003		
2009-11	10	0.170

Burned 2000 and 2013		
Before: 1992		
After	**df**	**p-value**
2009-11	15	0.134
2014	9	NA
Before: 2009-11		
2014	10	NA

Discussion

Vegetation Composition and Structure

The broad fire severity patterns are consistent with previous studies on the spatial distribution of fire severity in Linville Gorge (Wimberley & Reilly 2007; Waldrop et al. 2013). However, during field studies, fires have been observed to behave idiosyncratically in response to microtopography. High severity patches with bare soil exposure have been documented in otherwise low severity regions. This highly localized heterogeneity is not captured by Landsat images with coarser-scale capabilities, but may not be necessary to inform management decisions.

Across all NMS Axes, fire is a major driver of species composition and forest structure. Both fire severity and the number of burns a site experiences are ecologically important. Conversely, fire severity, as quantified by dNBR values, does not exhibit any significant correlations with environmental variables ($p>0.05$). This is likely to be attributable to the aforementioned idiosyncratic behavior of fires in Linville Gorge. Another possible explanation is that a per-pixel use of the dNBR severity images is not as accurate as a landscape-scale comparison. Inconsistent spatial resolutions of the environmental variables also could have contributed.

Species most correlated with NMS Axis 1 have varying site requirements, particularly with respect to fire needs, site slope, and site slope position. *Carya glabra* is common in Southern Appalachian woodlands (Weakley 2010), and often occurs in upland (Kirkman et al. 2007) forests that are dry to moist at lower elevations. *Fagus grandifolia* is another abundant species that occurs in moist forests at low elevations, mostly below 1,050 meters (Weakley 2010). *Amelanchier laevis* often occupies rocky woods and balds (Radford et al. 1968, Weakley 2010). Requiring fire for reproduction, *Pinus rigida* is found primarily on dry ridges, usually at elevations between 800 and 1,000 meters (Weakley 2010). In Linville Gorge, the characteristics required by *Amelanchier laevis* and *Pinus rigida* most typically are found in Montane Oak Forests and Rock Outcrops (Newell

1997). All of the 17 Montane Oak forests have experienced at least one fire, and all but three of the 11 surveyed Rock Outcrops have burned in recent history.

Likewise, species most correlated with NMS Axis 2 exhibit varying dependencies on disturbance levels, particularly *Paulownia tomentosa*, and often are restricted by site rockiness and/or elevation. *Paulownia tomentosa*, an invasive species native to China, is becoming increasingly common in human-impacted and disturbed areas, and has been observed encroaching in old growth forests. *Betula alleghaniensis* is common in Southern Appalachian woodlands at medium to high elevations, and is rarely seen at low elevations (Weakley 2010). *Ilex montana* is common in mesic forests (Weakley 2010), which often are documented at low and moderate elevations in Linville Gorge (Newell 1997). *Fothergilla major* typically is restricted to "dry ridgetop forests of middle elevation ridges in the mountains, especially along the Blue Ridge Escarpment, summits and upper slopes of Piedmont monadnocks, [and] northfacing bluffs in the lower Piedmont;" it is not a common species in Southern Appalachia (Weakley 2010). Sites meeting *Fothergilla major* habitat characteristics, such as Montane Oak forests, have experienced higher severity fires. The fires also are likely to have caused the death of *Fothergilla major* individuals.

NMS Axis 3 is similar to NMS Axis 2 in its important environmental variables. Species that load most heavily on this axis are restricted by moisture content of sites, which in turn determines the sites' burn severity and frequency (Waldrop et al. 2013). *Fraxinus americana* is common in North Carolina west of the Coastal Plain, on mesic slopes, drier calcareous or mafic glades and woodlands, and in rich cove forests. *Rhododendron periclymenoides* usually occupies stream banks and moist to dry slopes. Often co-occurring in *Rhododendron maximum* thickets, *Leucothoe fontanesiana* is plentiful on moist slopes, as well as on ravines and stream banks. Most widespread in the mountainous regions of Southern Appalachia, *Rhododendron minus* is not a moist-site species. Its typical range includes rocky slopes and escarpment gorges (Weakley 2010).

NMS Axis 4 is more difficult to interpret ecologically due to lack of correlation with environmental variables. Axis 4 is correlated only with Slope; otherwise variation is driven by fire. Species also exhibit less patterned relationships with each other, and with the end of Axis 4 on which they load. *Vitis aestivalis* is the single new species on this axis; it is widespread in mostly upland forests (Weakley 2010). With *Ilex montana*, dead *Vitis aestivalis* is most correlated with the fire severity end of Axis 4. Neither of these species occupies sites with need for higher severity fires. Rather, their habitats are likely to be distributed in Acid Cove and Slope Forests (Newell 1997) that will have burned with moderate to low severity. *Paulownia tomentosa* and *Fagus grandifolia* load on the other end of this axis that is correlated with slope. *Paulownia tomentosa* is found on steeper sites than *Fagus grandifolia*. Additionally, *Paulownia tomentosa's* abundance is correlated with increasing number of burns while *Fagus grandifolia* is a fire intolerant species.

Again, the ecological interpretation of NMS Axis 5 is challenging. It is related only to Slope, TCI, and the severity of the Shortoff fire. Similar to Axis 3, these species have specific moisture requirements, which is captured in part by TCI. *Rhus copallinum* is typical in dry woodlands and disturbed sites, as is *Aralia spinosa*. *Aralia spinosa* also occurs commonly in moist forests. *Quercus montana* is distributed in xeric forests on ridges and slopes (Weakley 2010). It is correlated with the same end of Axis 5—the one more correlated with TCI—as *Rhododendron periclymenoides*. The first species is typical on drier sites with fire histories, while the latter's habitat is in usually unburned streamside locations such as Rocky Streamside Shrublands (Newell 1997).

For Acid Cove and Slope, Xeric Evergreen, and Montane Oak Forests, variations in species composition and structure with fire are confirmed by the patterns of change vectors for NMS Axes 1 and 2. Additional observations of Alluvial Wetlands, Rocky Streamside Shrublands, Rich Cove and Slope Forests, and Rock Outcrops are necessary to evaluate their change trajectories with fire.

Restoration Goals

Fires have met some but not all of The Wilderness Society's restoration goals for Linville Gorge Wilderness Area. A decrease in the importance of ericaceous species with fire events achieves one of their targets. However, neither fire intolerant nor fire dependent species have behaved in the desired manner. Since fire intolerant species are not increasing in importance on unburned plots—only on those that have experienced fire—it is likely that fires have opened the understory for establishment of seeds or encouraged the sprouting of these species following disturbance. This finding is in line with past research on low burn frequency scenarios for prescribed fire regimes (Van Lear and Waldrop 1989).

Though they have not been observed to increase in the overstory data, fire dependent species of interest *Pinus rigida*, *Pinus pungens, Quercus alba, Quercus coccinea, Quercus rubra,* and *Quercus montana* all have been recorded in the woody regeneration data for the herbaceous layer (i.e. individuals below 1.4 meters tall) that has been collected by Waldrop et al. (2013).[2] Future monitoring should evaluate the growth of these individuals into canopy trees, ensuring that they are not out-competed by fire intolerant species. Decreases in overstory individuals of these species both with and without fire also should be kept in mind for burn management plans, as high severity ridge fires may have contributed to tree deaths, particularly of *Pinus rigida* and *Pinus pungens*.

The Linville vegetation dataset largely would suggest that *Paulownia tomentosa* has not increased in abundance with fire. However, this lack of evidence for increases is not consistent with reports from local experts or volunteer groups (Ben Prater, Conservation Director for Wild South, personal conversation). Again, continued monitoring efforts are necessary to evaluate the encroachment of *Paulownia tomentosa* and other invasive species into Linville's native plant communities.

[2] Woody regeneration data (i.e. only for woody plant species) was collected at the one meter intensively sampled corners described in the CVS protocol (Peet et al. 1998). Because of species identification difficulties for the other field crews, no woody regeneration data was collected in 2003 or 2014.

Conclusion

While diversity of plant species and communities in Linville Gorge Wilderness Area has persisted with the absence of regular fire (Newell 1997, Waldrop et al. 2013), recent burns have acted to increase the heterogeneity of species composition and structure. If the use of prescribed fire in Linville Gorge is pursued, results should be monitored for achievement of desirable outcomes. This is particularly important for the spread of invasive organisms, as well as for the resurgence of fire dependent species. Prescribed fire plans also should be mindful of the return interval for burns. Frequent fires may be required to achieve restoration goals and to discourage increases in importance of fire intolerant species. If resources will limit the duration of the burn program, managers should consider carefully the commencement of the initiative. Introducing fire only temporarily could act to encourage the concurrent expansion of fire intolerant species with the mortality of fire dependent species, particularly on ridges with *Pinus pungens* and *Pinus rigida* that are prone to high severity fires.

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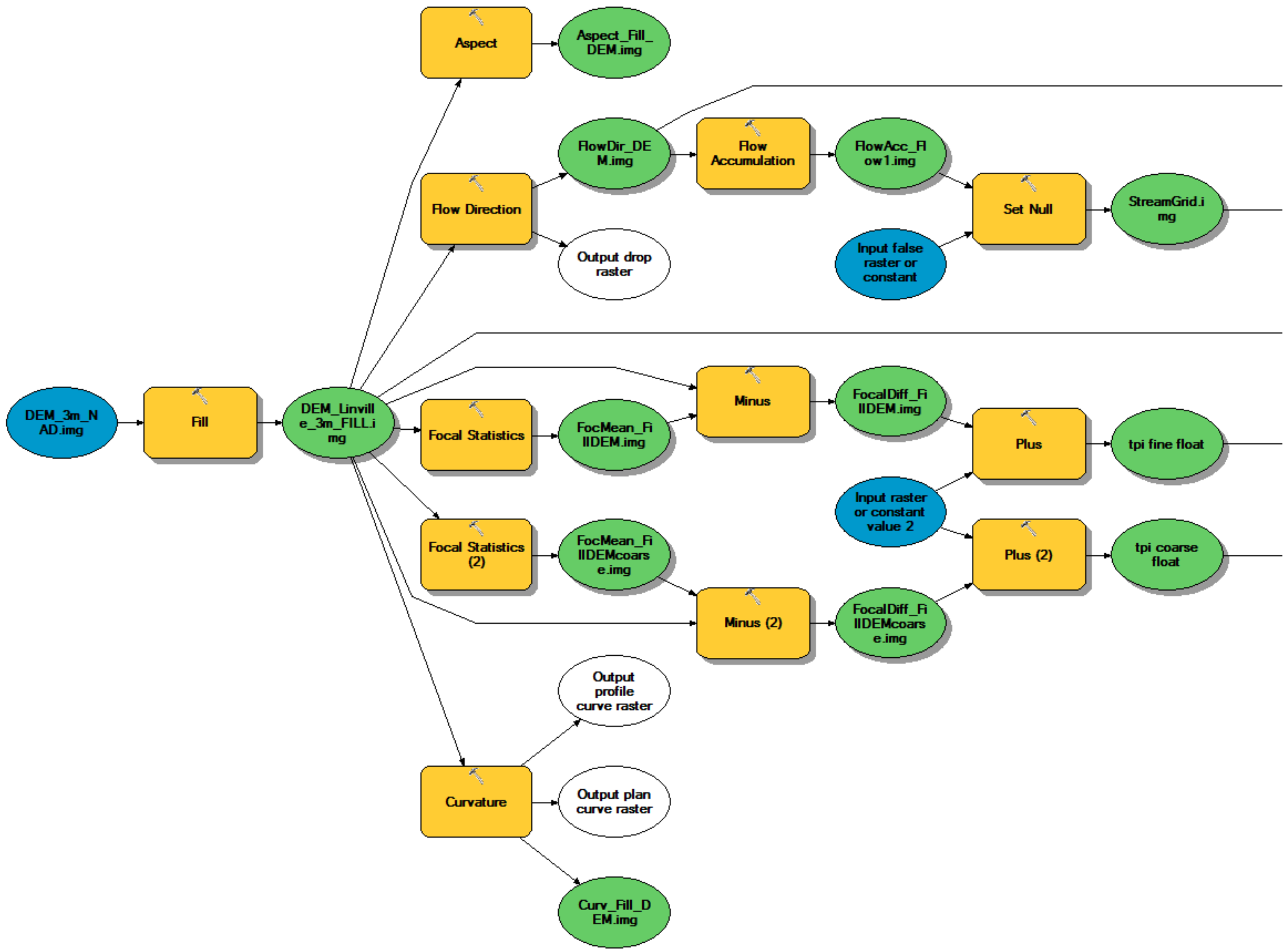
APPENDIX A

Table 1: Species included in Objective 1 analyses.

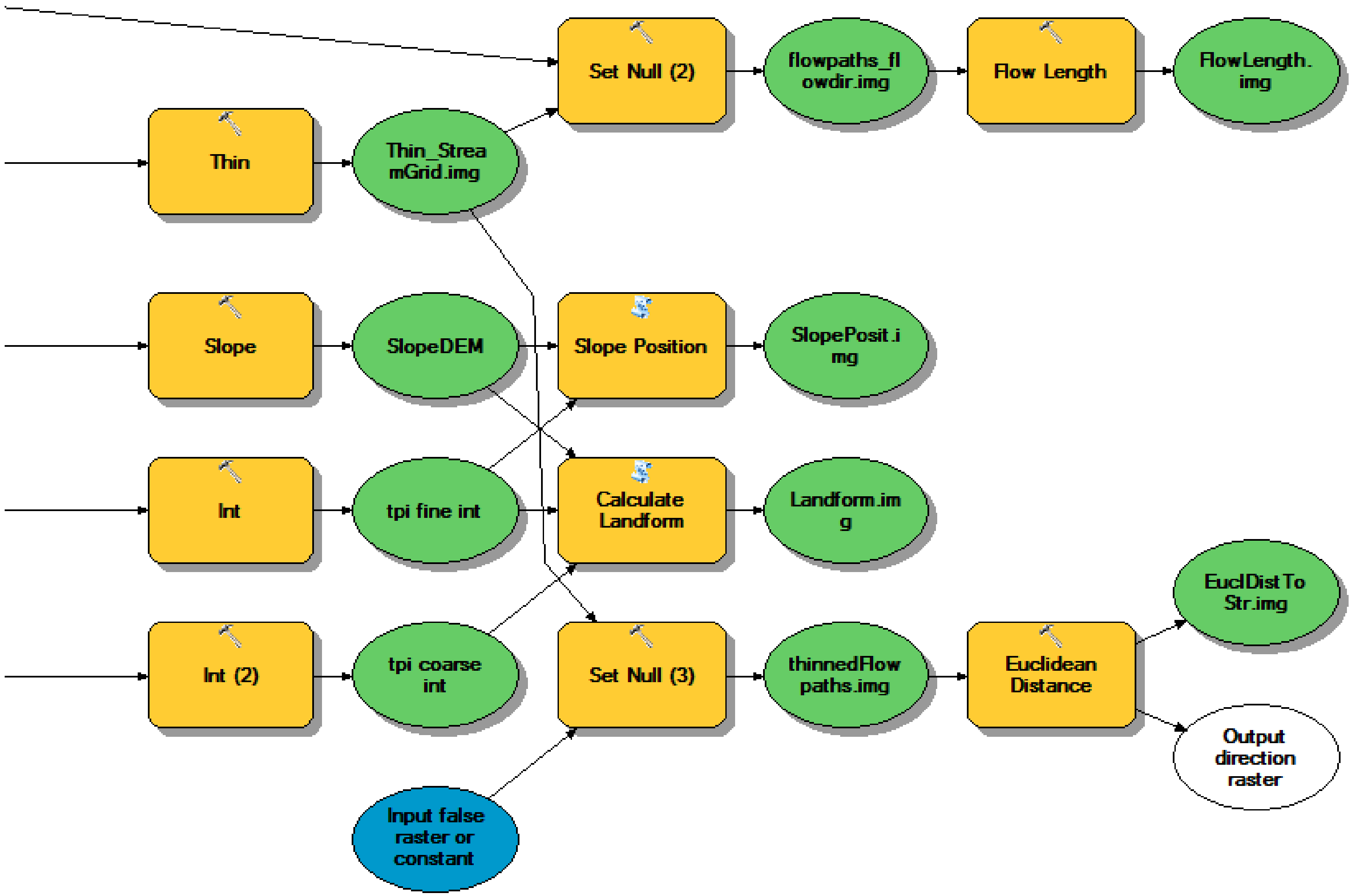
Species	***Scientific Name***	**Common Name**	**Growth Form**
ACERPEN	*Acer pensylvanicum*	Striped Maple	Tree
ACERRUB	*Acer rubrum*	Red Maple	Tree
AMELARB	*Amelanchier arborea*	Common Serviceberry	Tree
AMELLAE	*Amelanchier laevis*	Allegheny Serviceberry	Tree/Shrub
ARALSPI	*Aralia spinosa*	Devil's Walking Stick	Shrub
BETUALL	*Betula alleghaniensis*	Yellow Birch	Tree
BETULEN	*Betula lenta*	Sweet Birch, Black Birch	Tree
CARYALB	*Carya alba*	Mockernut Hickory	Tree
CARYGLA	*Carya glabra*	Pignut Hickory	Tree
CASTDEN	*Castanea dentata*	American Chestnut	Tree
CASTPUM	*Castanea pumila*	Allegheny Chinkapin	Shrub
CLETACU	*Clethra acuminata*	Mountain Sweetpepperbush	Shrub
CORNFLO	*Cornus florida*	Flowering Dogwood	Tree
DIOSVIR	*Diospyros virginiana*	Persimmon	Tree
EUBOREC	*Eubotrys recurva*	Redtwig Doghobble	Shrub
FAGUGRA	*Fagus grandifolia*	American Beech	Tree
FOTHMAJ	*Fothergilla major*	Mountain Witchalder	Shrub
FRAXAME	*Fraxinus americana*	White Ash	Tree
HALETET	*Halesia tetraptera*	Mountain Silverbell	Tree
HAMAVIR	*Hamamelis virginiana*	American Witchhazel	Tree
HDWDSPP	Hardwood species	Hardwood species	Tree
ILEXMON	*Ilex montana*	Mountain Holly	Shrub
ILEXOPA	*Ilex opaca*	American Holly	Tree
KALMLAT	*Kalmia latifolia*	Mountain Laurel	Shrub
LEUCFON	*Leucothoe fontanesiana*	Highland Dog Hobble	Shrub
LEUCREC	*Leucothoe recurva*	Redtwig Dog Hobble	Shrub
LIQUSTY	*Liquidambar styraciflua*	Sweetgum	Tree
LIRITUL	*Liriodendron tulipifera*	Tuliptree, Yellow-poplar	Tree
LYONLIG	*Lyonia ligustrina*	Maleberry	Shrub
MAGNFRA	*Magnolia fraseri*	Fraser Magnolia	Tree
NYSSSYL	*Nyssa sylvatica*	Blackgum	Tree
OXYDARB	*Oxydendrum arboreum*	Sourwood	Tree
PARTQUI	*Parthenocissus quinquefolia*	Virginia Creeper	Vine
PAULTOM	*Paulownia tomentosa*	Princesstree, Paulownia	Tree
PINUPUN	*Pinus pungens*	Table Mountain Pine	Tree
PINURIG	*Pinus rigida*	Pitch Pine	Tree
PINUSPP	Pinus species	Pine	Tree

Species	Scientific Name	Common Name	Growth Form
PINUSTR	*Pinus strobus*	White Pine	Tree
PINUVIR	*Pinus virginiana*	Virginia Pine	Tree
PRUNPEN	*Prunus pensylvanica*	Pin Cherry	Tree
PYRUPUB	*Pyrularia pubera*	Buffalo Nut	Shrub
QUERALB	*Quercus alba*	White Oak	Tree
QUERCOC	*Quercus coccinea*	Scarlet Oak	Tree
QUERMON	*Quercus montana*	Chestnut Oak	Tree
QUERPRI	*Quercus prinus*	Chestnut Oak	Tree
QUERRUB	*Quercus rubra*	Northern Red Oak	Tree
QUERVEL	*Quercus velutina*	Black Oak	Tree
RHODCAT	*Rhododendron catawbiense*	Catawba Rosebay	Shrub
RHODMAX	*Rhododendron maximum*	Great Laurel, Rosebay	Shrub
RHODMIN	*Rhododendron minus*	Piedmont Rhododendron	Shrub
RHODPER	*Rhododendron periclymenoides*	Pink Azalea, Pinxterbloom	Shrub
RHUSCOP	*Rhus copallinum*	Winged Sumac	Shrub
RHUSGLA	*Rhus glabra*	Smooth Sumac	Shrub
ROBIHIS	*Robinia hispida*	Bristly Locust	Shrub
ROBIPSE	*Robinia pseudoacacia*	Black Locust	Tree
RUBUARG	*Rubus argutus*	Sawtooth Blackberry	Shrub
RUBUSPP	Rubus species	Blackberry species	Shrub
SASSALB	*Sassafras albidum*	Sassafras	Tree
SMILGLA	*Smilax glauca*	Cat Greenbrier	Herb
SMILROT	*Smilax rotundifolia*	Roundleaf Greenbrier	Herb
SYMPTIN	*Symplocos tinctoria*	Common Sweetleaf, Horsesugar	Shrub
TSUGCAN	*Tsuga canadensis*	Eastern Hemlock	Tree
TSUGCAR	*Tsuga caroliniana*	Carolina Hemlock	Tree
TSUGSPP	Tsuga species	Hemlock species	Tree
VACCCOR	*Vaccinium corymbosum*	Highbush Blueberry	Shrub
VACCPAL	*Vaccinium pallidum*	Blue Ridge Blueberry	Shrub
VACCSIM	*Vaccinium simulatum*	Upland Highbush Blueberry	Shrub
VACCSTA	*Vaccinium stamineum*	Deerberry	Shrub
VITIAES	*Vitis aestivalis*	Summer grape	Vine

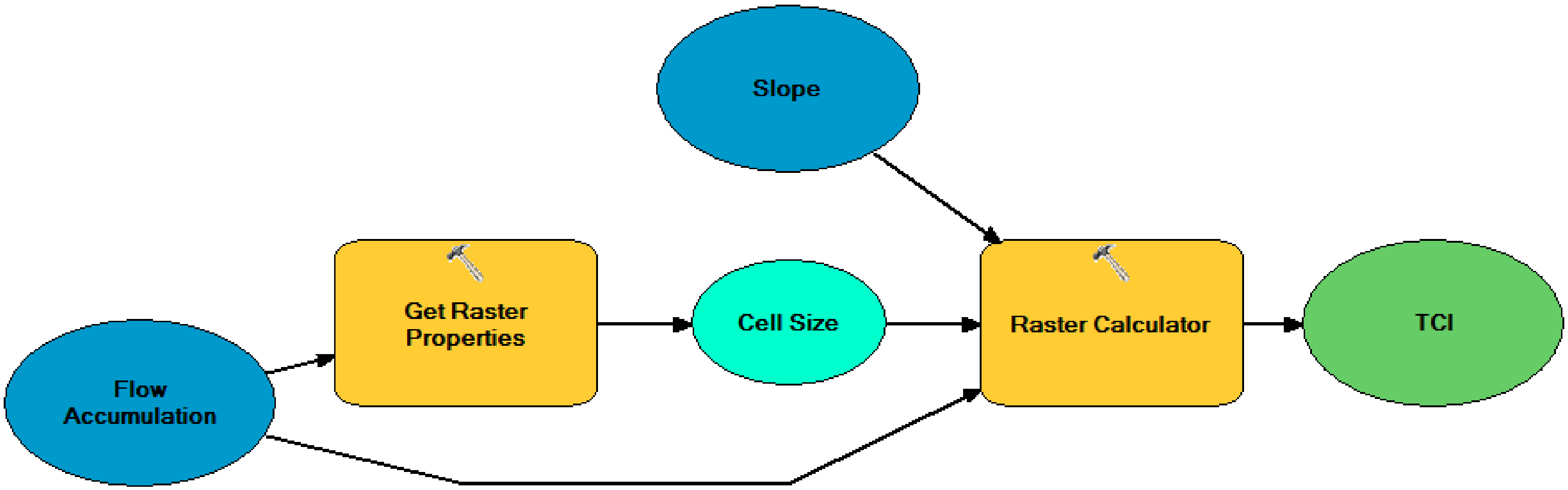
APPENDIX B



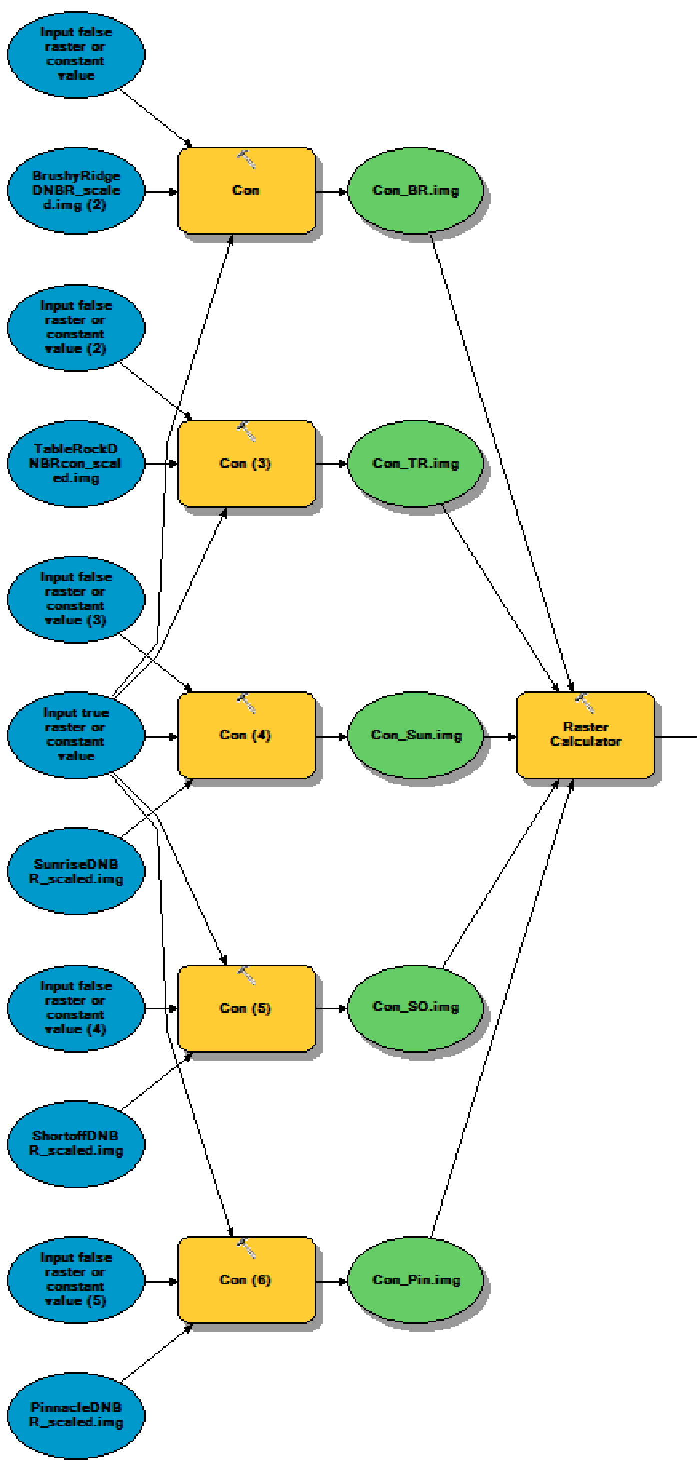
Model 1a: Generation of DEM variables



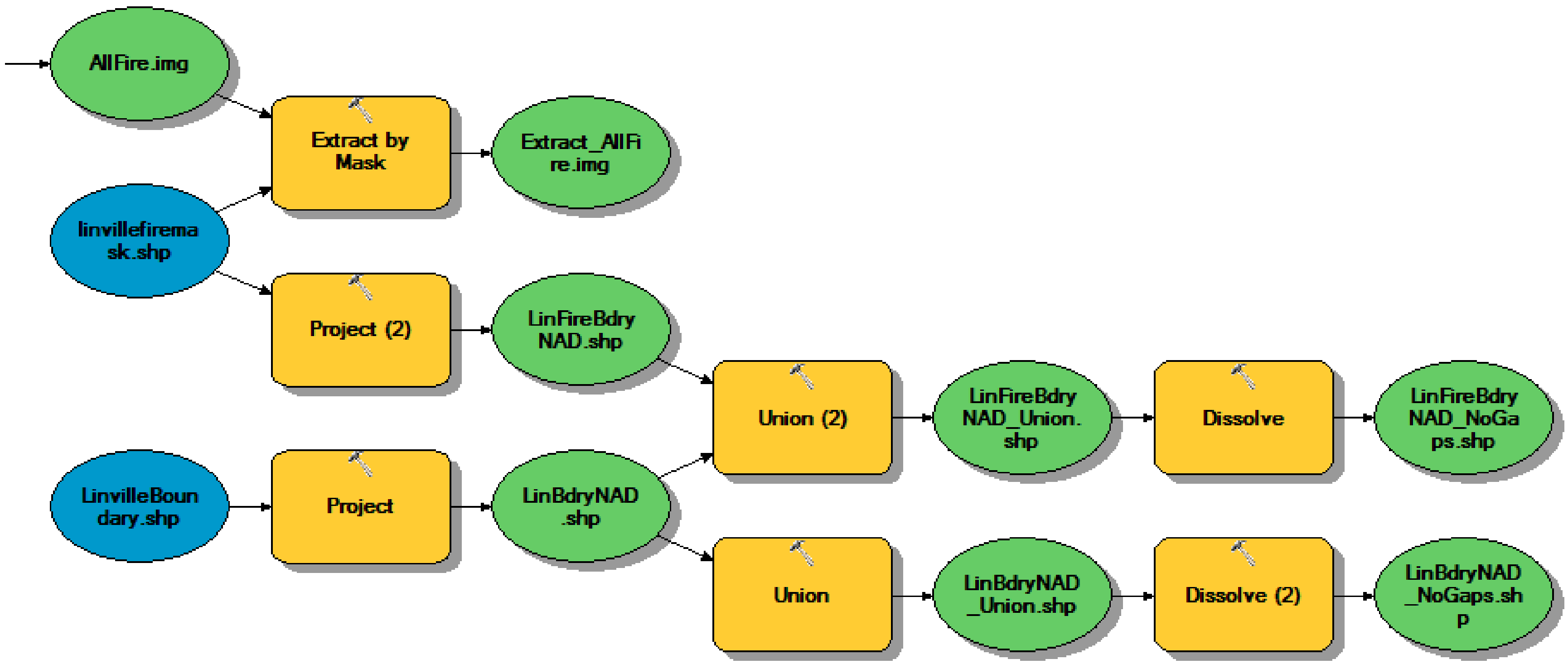
Model 1b: Generation of DEM variables.



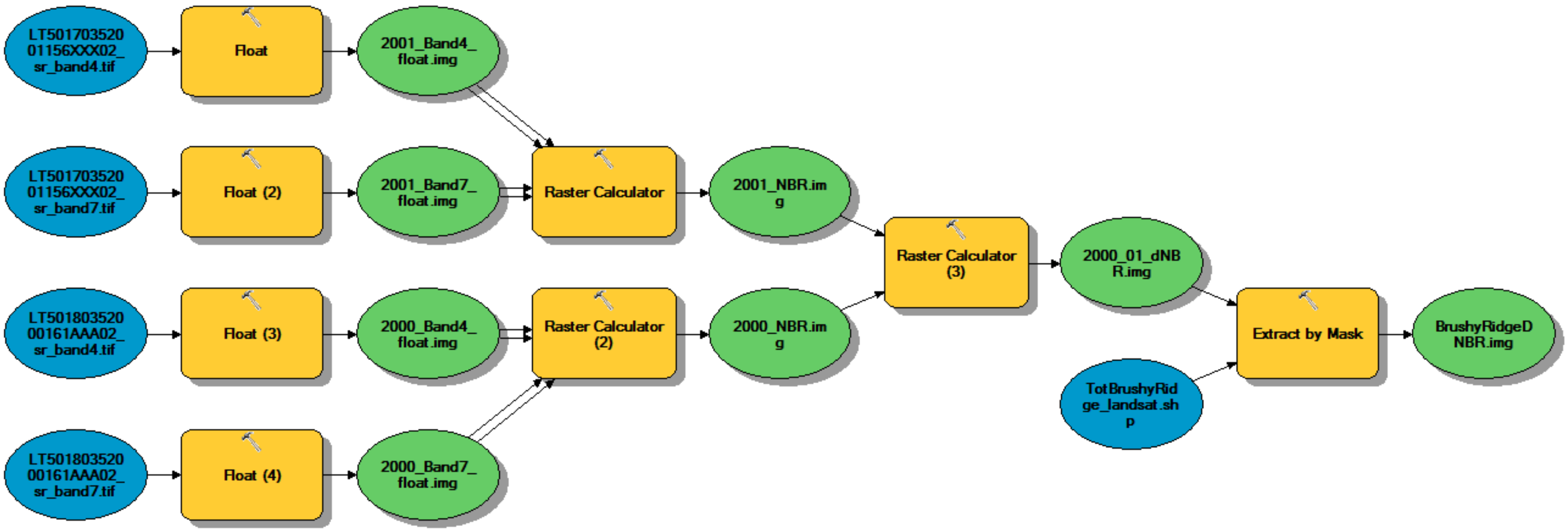
Model 1c: Generation of environmental variables (TCI model created by John Fay, Duke University).



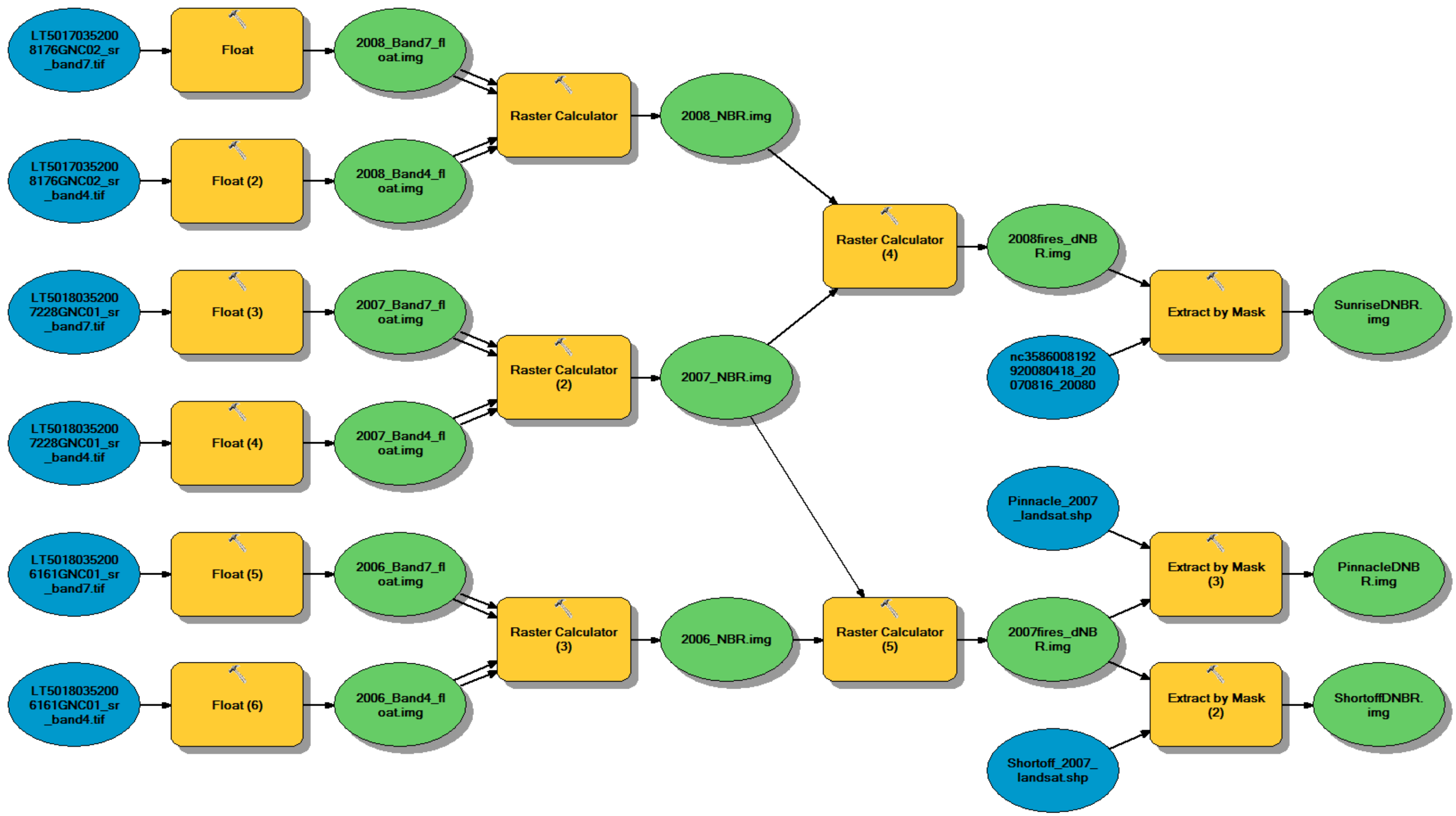
Model 2a: Creation of burn histories.



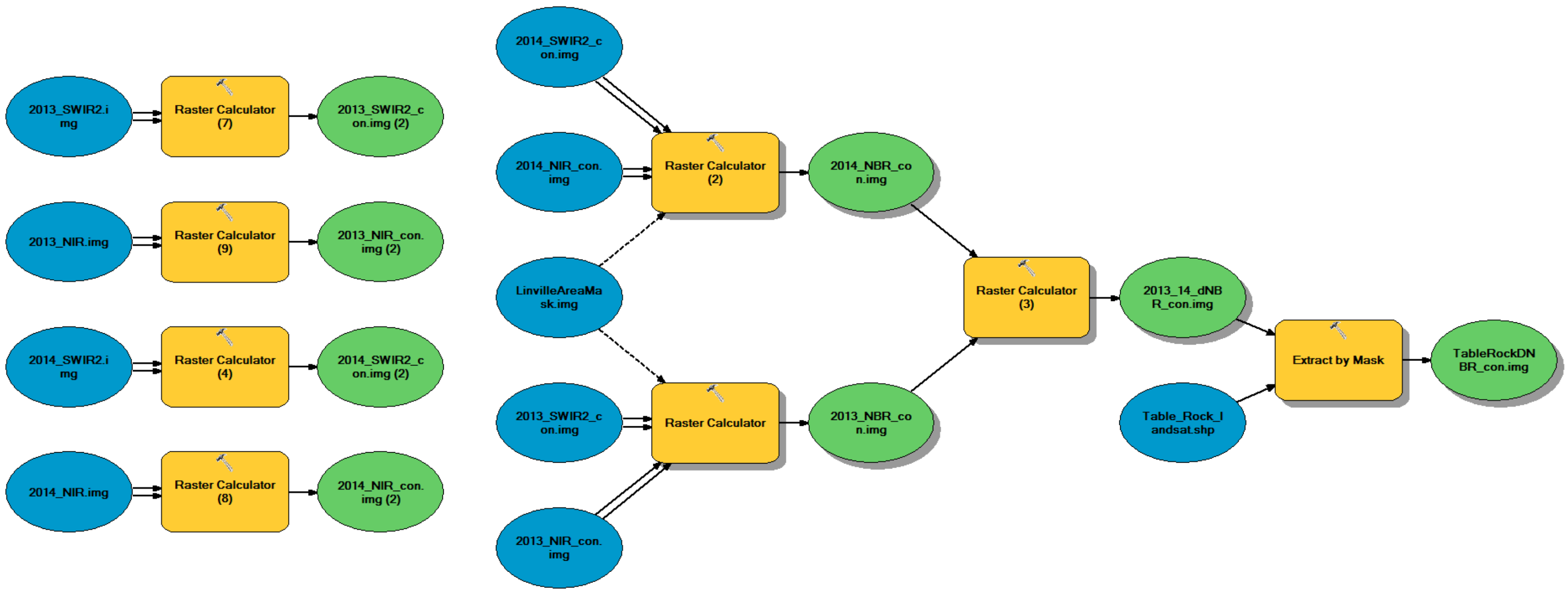
Model 2b: Creation of burn histories.



Model 3a: Generation of Brushy Ridge dNBR images.



Model 3b: Generation of Sunrise, Pinnacle, and Shortoff dNBR images.



Model 3c: Generation of Table Rock dNBR image with negative image values removed.

Model 4: Extraction of environmental variable and dNBR values to Linville plot point locations (USFS, unpublished data).

```
# ---------------------------------------------------------------------------
# extracttopoints.py
# Created on: 2015-04-22 20:24:40.00000
#   (generated by ArcGIS/ModelBuilder)
# Description:
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "G:\\MastersProject\\Linville_GISdata\\Scratch"
arcpy.env.workspace = "G:\\MastersProject\\Linville_GISdata\\Data"

# Local variables:
Geol_Linville_NAD_shp = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Geol_Linville_NAD.shp"
SoilMU_a_NAD_Clip_shp = "G:\\MastersProject\\Linville_GISdata\\Scratch\\SoilMU_a_NAD_Clip.shp"
Linville_Plots_EnvVars_shp = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Linville_Plots_EnvVars.shp"
Aspect_Fill_DEM_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Aspect_Fill_DEM.img"
Curv_Fill_DEM_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Curv_Fill_DEM.img"
DEM_Linville_3m_FILL_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\DEM_Linville_3m_FILL.img"
EuclDistToStr_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\EuclDistToStr.img"
FlowLength_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\FlowLength.img"
Landform_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Landform.img"
RelSlopePos_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\RelSlopePos.img"
Slope_Deg_Fill_DEM_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Slope_Deg_Fill_DEM.img"
SlopePosit_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\SlopePosit.img"
TCI_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\TCI.img"
TPI_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\TPI.img"
BrushyRidgeDNBR_img = "G:\\MastersProject\\RSfinalProject\\Landsat\\2000fires\\NBR\\BrushyRidgeDNBR.img"
PinnacleDNBR_img = "G:\\MastersProject\\RSfinalProject\\Landsat\\2007_2008fires\\dNBR\\PinnacleDNBR.img"
ShortoffDNBR_img = "G:\\MastersProject\\RSfinalProject\\Landsat\\2007_2008fires\\dNBR\\ShortoffDNBR.img"
SunriseDNBR_img = "G:\\MastersProject\\RSfinalProject\\Landsat\\2007_2008fires\\dNBR\\SunriseDNBR.img"
TableRockDNBR_img = "G:\\MastersProject\\RSfinalProject\\Landsat\\2013fire\\dNBR\\TableRockDNBR.img"
Geol_Lin_NAD_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Geol_Lin_NAD.img"
Soil_Lin_NAD_img = "G:\\MastersProject\\Linville_GISdata\\Scratch\\Soil_Lin_NAD.img"

# Process: Polygon to Raster
arcpy.PolygonToRaster_conversion(Geol_Linville_NAD_shp, "ORIG_LABEL", Geol_Lin_NAD_img, "CELL_CENTER",
"NONE", "3")

# Process: Polygon to Raster (3)
arcpy.PolygonToRaster_conversion(SoilMU_a_NAD_Clip_shp, "MUSYM", Soil_Lin_NAD_img, "CELL_CENTER",
"NONE", "3")
```

```
# Process: Extract Multi Values to Points
arcpy.gp.ExtractMultiValuesToPoints_sa(Linville_Plots_EnvVars_shp,
"G:\\MastersProject\\Linville_GISdata\\Scratch\\Aspect_Fill_DEM.img
Aspect_Fil;G:\\MastersProject\\Linville_GISdata\\Scratch\\Curv_Fill_DEM.img
Curv_Fill_;G:\\MastersProject\\Linville_GISdata\\Scratch\\DEM_Linville_3m_FILL.img
DEM_Linvil;G:\\MastersProject\\Linville_GISdata\\Scratch\\EuclDistToStr.img
EuclDistTo;G:\\MastersProject\\Linville_GISdata\\Scratch\\FlowLength.img
FlowLength;G:\\MastersProject\\Linville_GISdata\\Scratch\\Landform.img
Landform;G:\\MastersProject\\Linville_GISdata\\Scratch\\RelSlopePos.img
RelSlopePo;G:\\MastersProject\\Linville_GISdata\\Scratch\\Slope_Deg_Fill_DEM.img
Slope_Deg_;G:\\MastersProject\\Linville_GISdata\\Scratch\\SlopePosit.img
SlopePosit;G:\\MastersProject\\Linville_GISdata\\Scratch\\TCI.img
TCI;G:\\MastersProject\\Linville_GISdata\\Scratch\\TPI.img
TPI;G:\\MastersProject\\RSfinalProject\\Landsat\\2000fires\\NBR\\BrushyRidgeDNBR.img
BrushyRidg;G:\\MastersProject\\RSfinalProject\\Landsat\\2007_2008fires\\dNBR\\PinnacleDNBR.img
PinnacleDN;G:\\MastersProject\\RSfinalProject\\Landsat\\2007_2008fires\\dNBR\\ShortoffDNBR.img
ShortoffDN;G:\\MastersProject\\RSfinalProject\\Landsat\\2007_2008fires\\dNBR\\SunriseDNBR.img
SunriseDNB;G:\\MastersProject\\RSfinalProject\\Landsat\\2013fire\\dNBR\\TableRockDNBR.img
TableRockD;G:\\MastersProject\\Linville_GISdata\\Scratch\\Geol_Lin_NAD.img
Geol_Lin_N;G:\\MastersProject\\Linville_GISdata\\Scratch\\Soil_Lin_NAD.img Soil_Lin_N", "NONE")
```

APPENDIX C

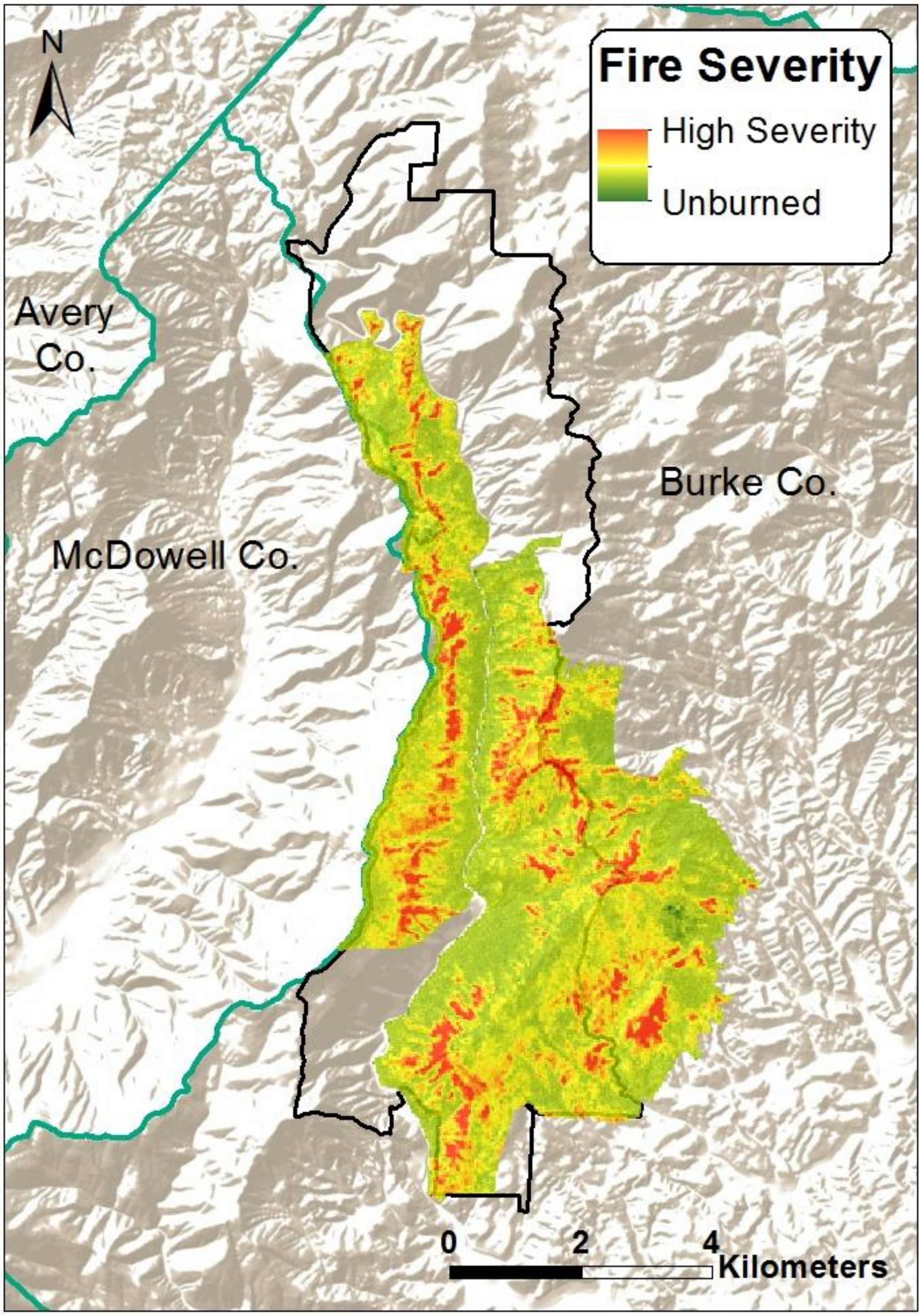


Figure 1: The 2000 Brushy Ridge fire extent and dNBR severity.

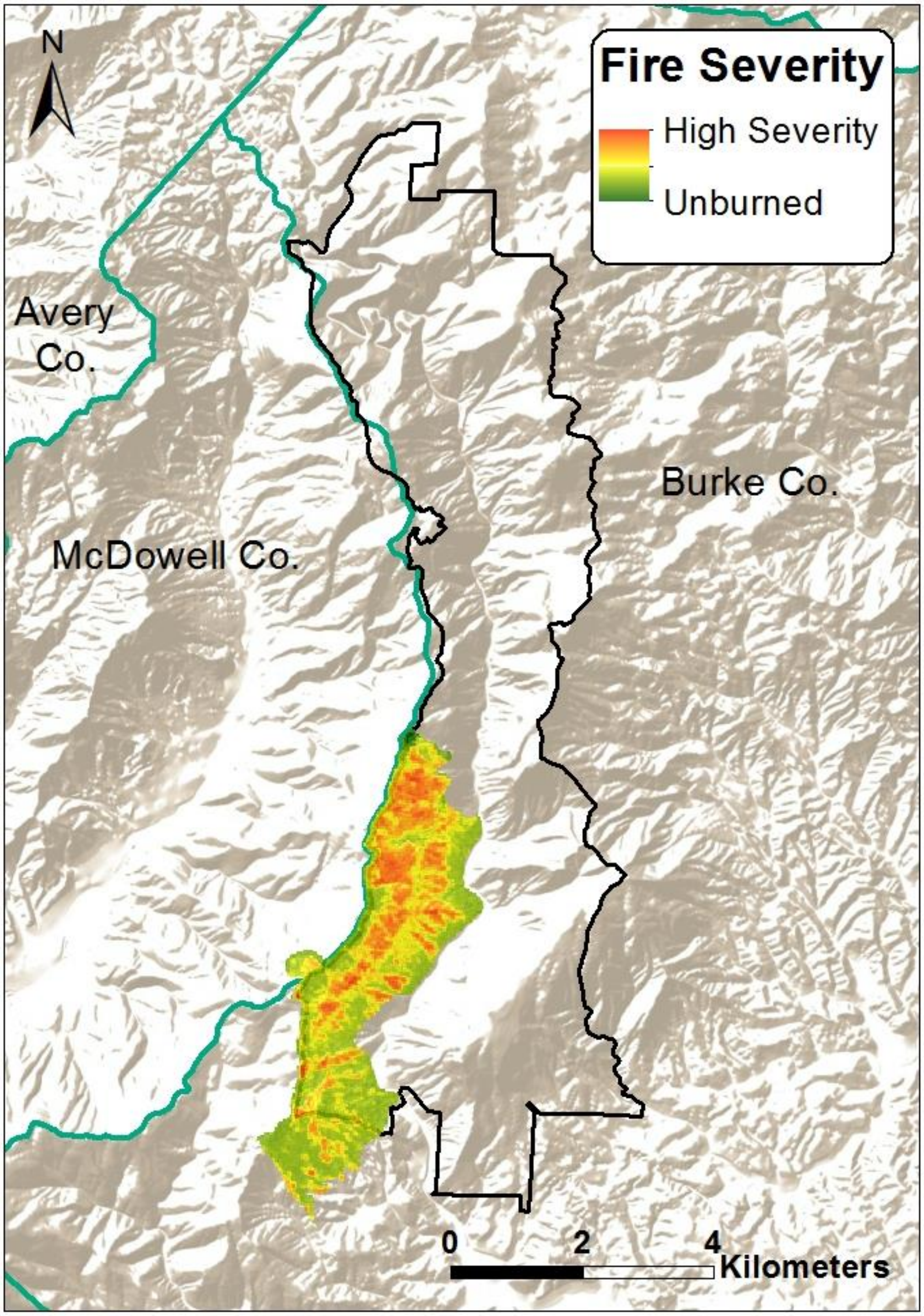


Figure 2: The 2007 Pinnacle fire extent and dNBR severity.

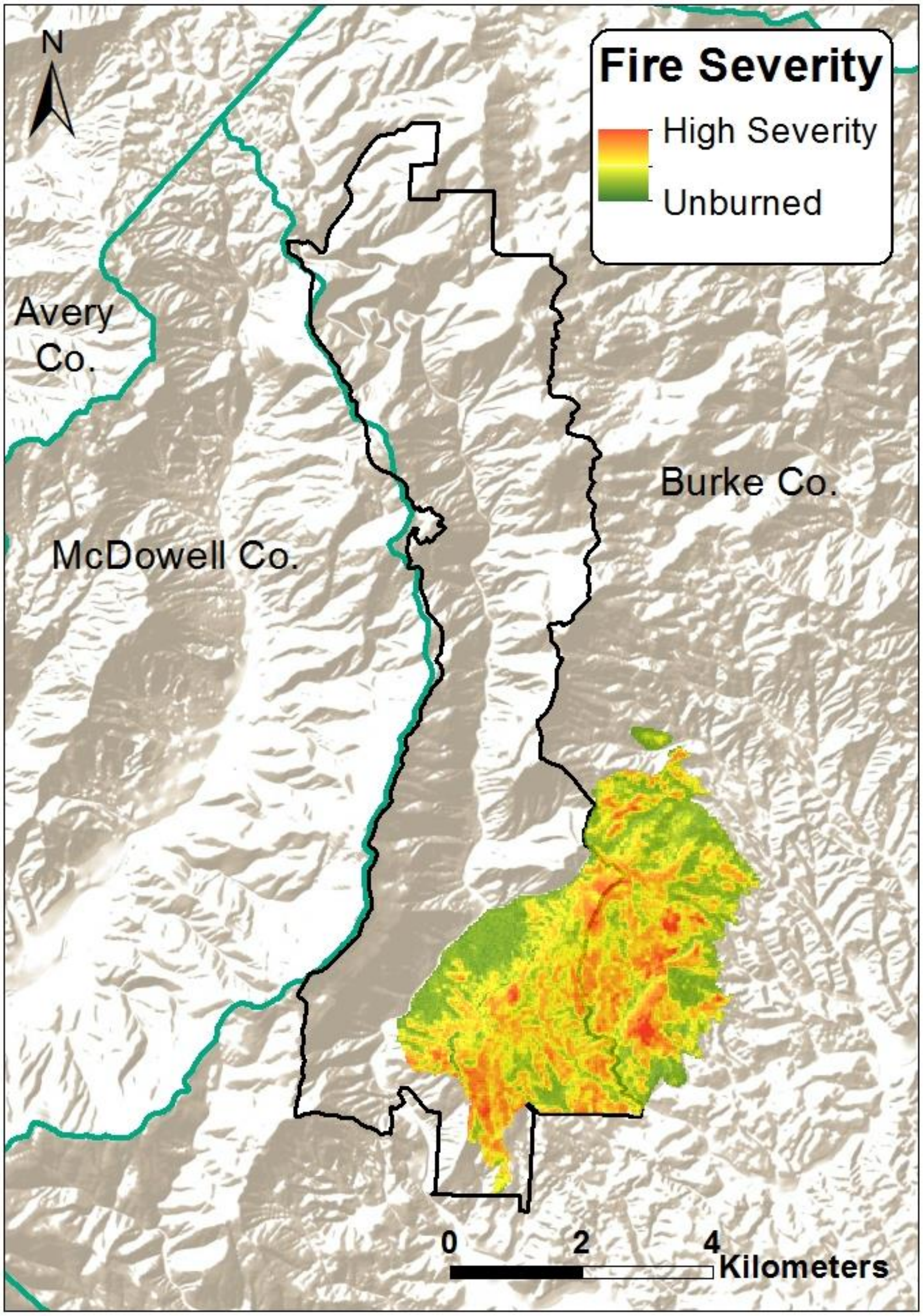


Figure 3: The 2007 Shortoff fire extent and dNBR severity.

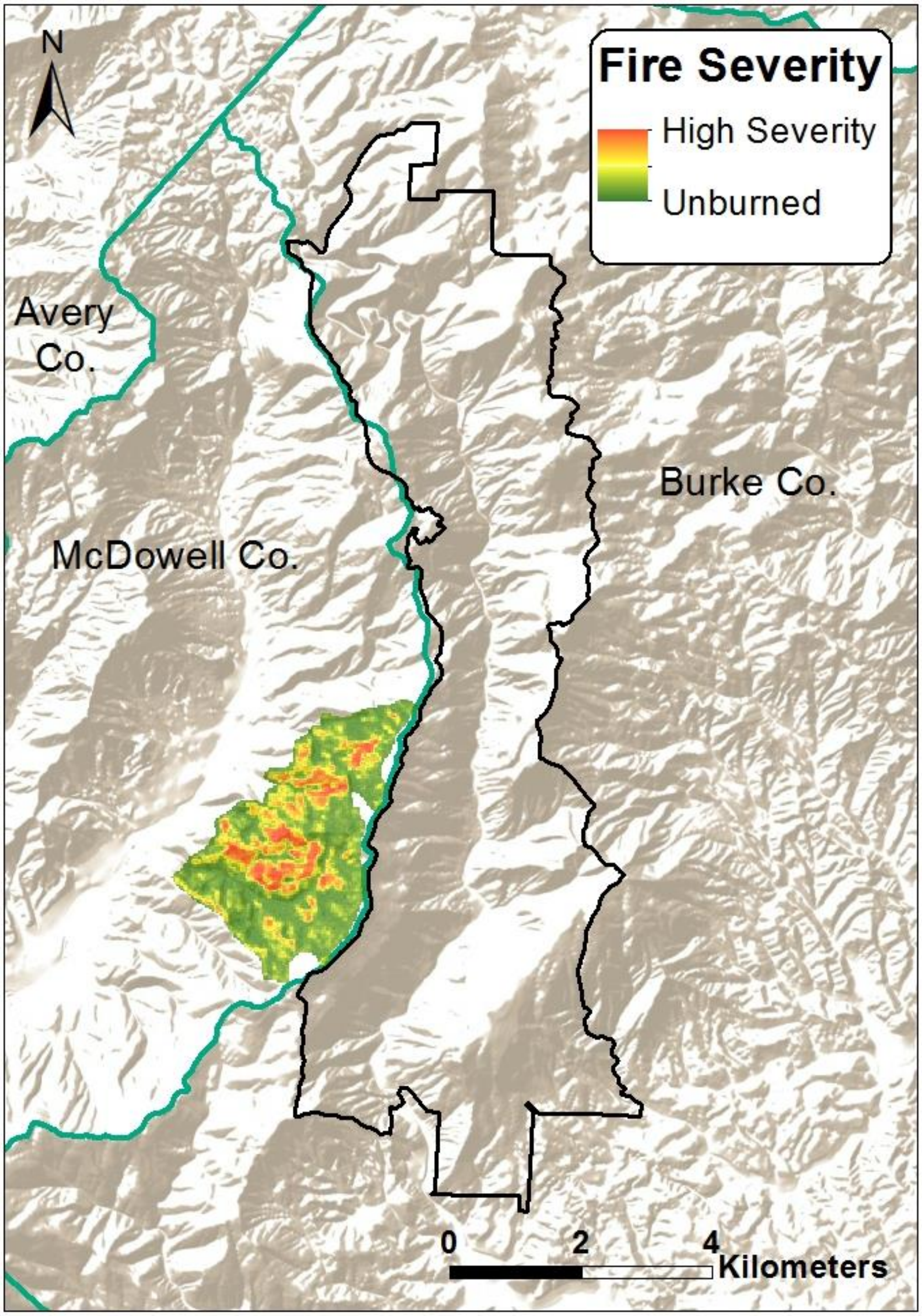


Figure 4: The 2008 Sunrise fire extent and dNBR severity.

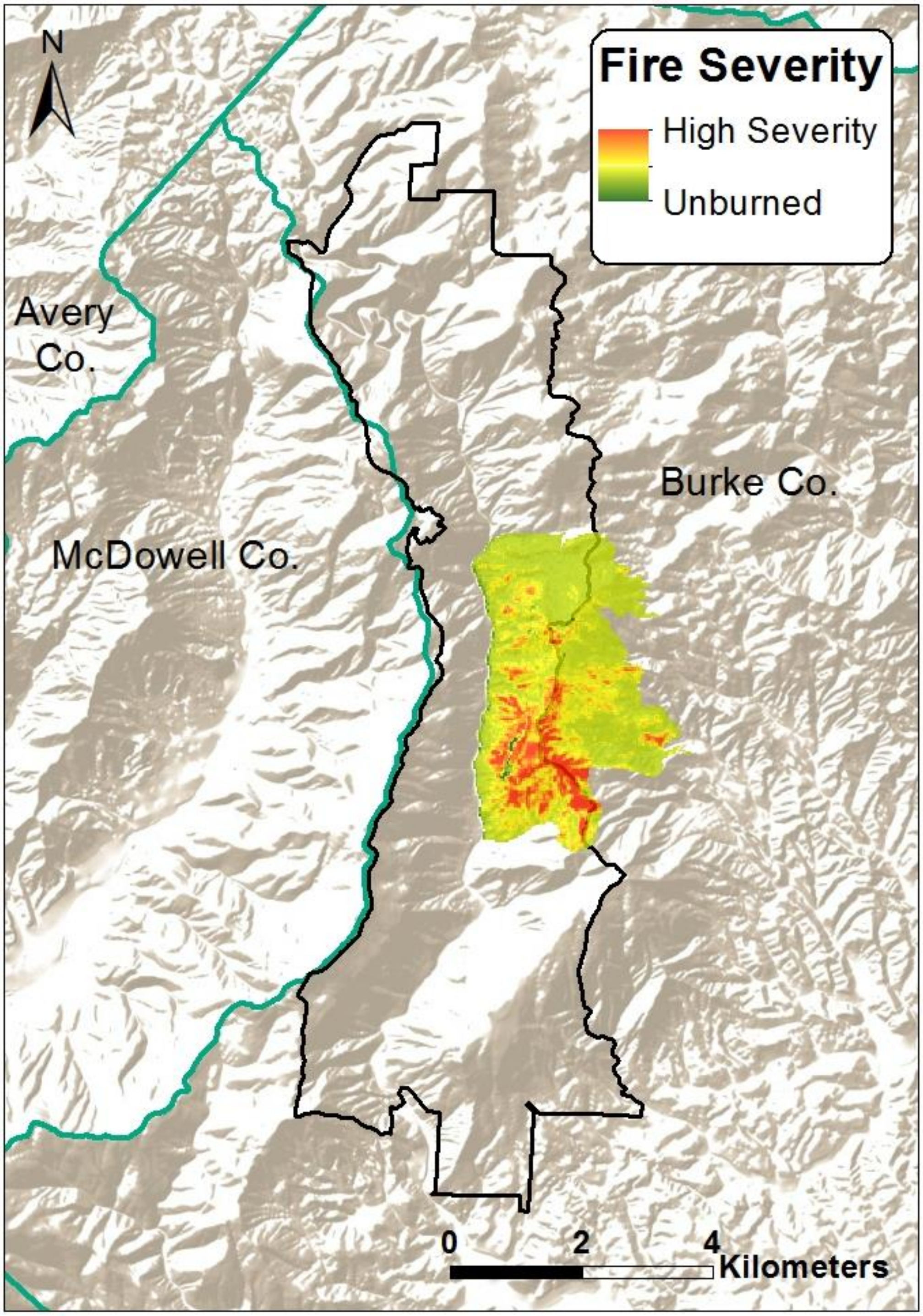


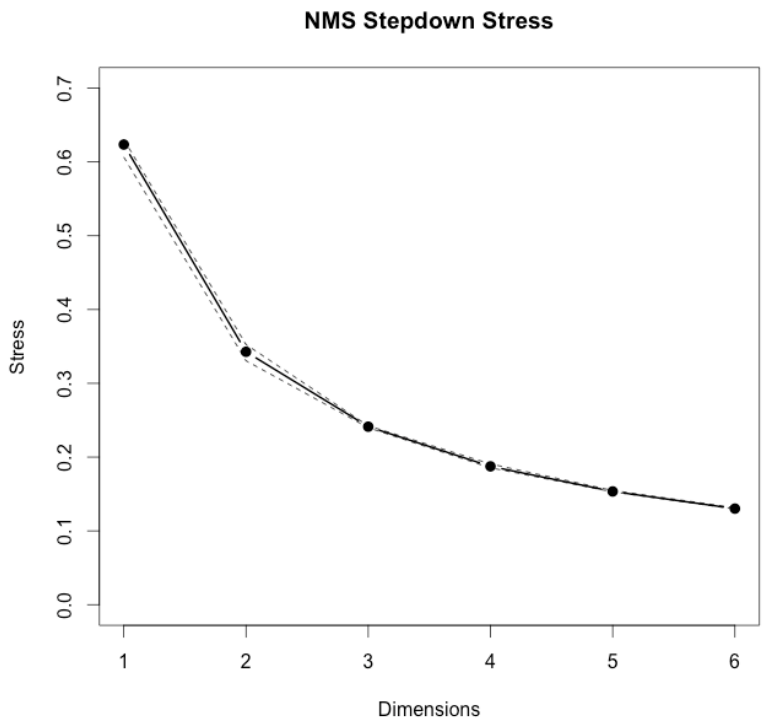
Figure 5: The 2013 Table Rock fire extent and dNBR severity.

APPENDIX D

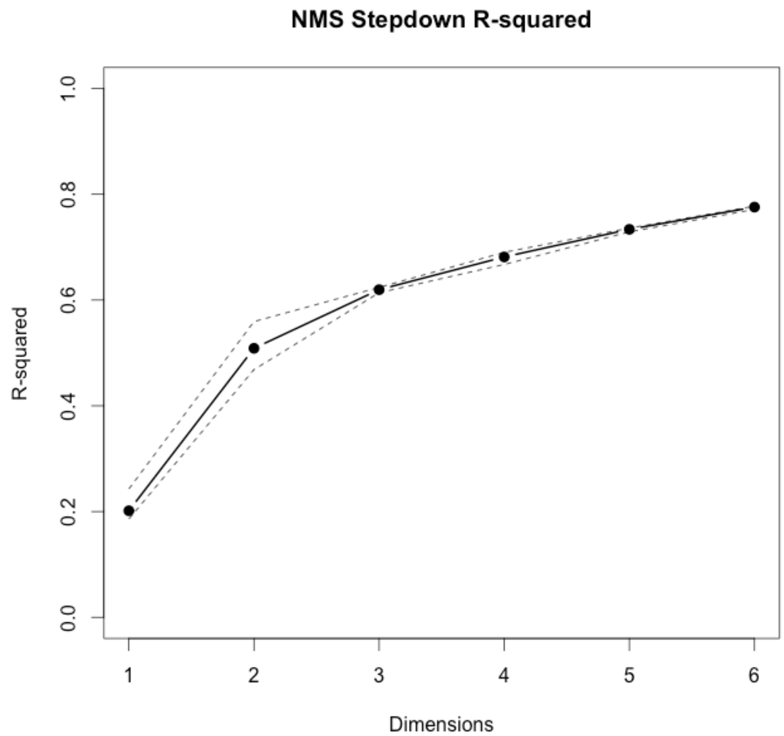
Vegetation Composition and Structure Analyses

R code for NMS analysis and change vectors adapted from Dean Urban, PhD, Duke University.

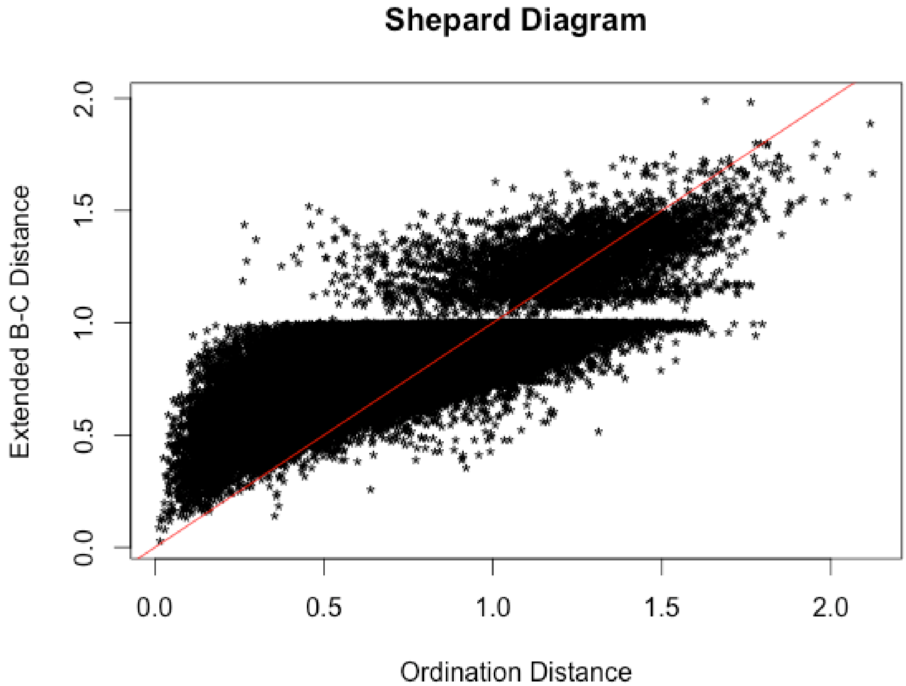
```
setwd("~/Desktop/DataAnalysis")
sppdata <- read.csv("DATA_AllInfo_NoRare.csv")
envvars1<- read.csv("DATA_NoRare_envvarsNMS1.csv",header=TRUE)
envvars2<- read.csv("DATA_NoRare_envvarsNMS2.csv",header=TRUE)
#envvars3<- read.csv("DATA_NoRare_Cor5_envvars.csv",header=TRUE)
env.cor<-cor(envvars[,-1:-2], envvars[,-1:-2])
env.cor.matrix<-as.matrix(env.cor)
write.csv(env.cor.matrix, "env.cor.table.csv")
# check to make sure that data loaded properly
names(sppdata[,-1:-4])
sppdata$Plot_Year

library(vegan)

# Use vegan to do B-C distances and step-across function:
sppdata.bcd<-vegdist(sppdata[,-1:-4],method="bray")

# Extended distances, as stepping-stone paths:
sppdata.xbcd<-stepacross(sppdata.bcd, path="extended")

# a step-down procedure in ECODIST ...
detach(package:vegan, unload=T)
library(ecodist)

# Generate 50 ordinations, stepdown:
spp.nms.step <- nmds(sppdata.xbcd, nits=10, mindim=1, maxdim=6)
attributes(spp.nms.step)

# Pull out the stress values, as a matrix (rows=dimensions):
spp.nms.stress <- matrix(spp.nms.step$stress, nrow=6, byrow=T)
nms.stress.mean <- apply(spp.nms.stress, 1, "mean")
nms.stress.min <- apply(spp.nms.stress, 1, "min")
nms.stress.max <- apply(spp.nms.stress, 1, "max")

# Scree plot:
plot(1:6, nms.stress.mean, type="b", pch=19, lwd=2, xlab="Dimensions", ylim=c(0, 0.7), ylab="Stress")
lines(1:6, nms.stress.min, type="l", lty=2)
lines(1:6, nms.stress.max, type="l", lty=2)
title("NMS Stepdown Stress")
```




```
# Ditto, for R2:
spp.nms.r2 <- matrix(spp.nms.step$r2, nrow=6, byrow=T)
nms.r2.mean <- apply(spp.nms.r2, 1, "mean")
nms.r2.min <- apply(spp.nms.r2, 1, "min")
nms.r2.max <- apply(spp.nms.r2, 1, "max")

# Scree plot:
plot(1:6, nms.r2.mean, type="b", pch=19, lwd=2, xlab="Dimensions", ylim=c(0, 1.0), ylab="R-squared")
lines(1:6, nms.r2.min, type="l", lty=2)
lines(1:6, nms.r2.max, type="l", lty=2)
title("NMS Stepdown R-squared")
```

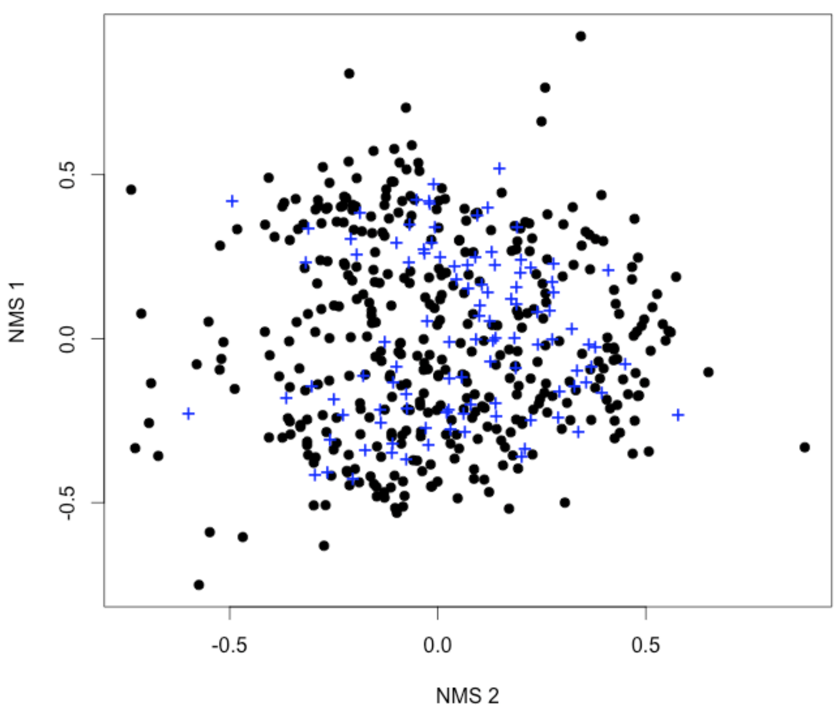



```
# Do a final configuration ...
# does 100 reps (iterations), for 5 dimensions:
spp.nmds <- nmds(sppdata.xbcd,mindim=5,maxdim=5,nits=100)

# Find iteration with minimum stress
s.min <- which.min(spp.nmds$stress) # returns might be different
spp.nmds$stress[s.min] # returns the stress for the best one;
# note this is scaled on [0,1], not [0,100] as with VEGAN and PC-Ord
spp.nms.StressMin <- nmds.min(spp.nmds) # grabs the best of 100 reps

##########################################
# Rotate the NMS ordination ...
# This also forces axis 1 to have the most variance, etc.
nms.pca<-princomp(spp.nms.StressMin)
print(nms.pca)
summary(nms.pca)
spp.nms.pca_scores<-nms.pca$scores
colnames(spp.nms.pca_scores) <- c("NMS1", "NMS2" , "NMS3", "NMS4", "NMS5")
colnames(spp.nms.pca_scores)
##########################################
?tapply
# Plot the Shepard diagram:
nms2.xod<-dist(spp.nms.pca_scores)

plot(nms2.xod,sppdata.xbcd,pch="*",xlab="Ordination Distance", ylab="Extended B-C Distance")
abline(0,1,col="red") # put in the 1:1 line (intercept=0, slope=1)
title("Shepard Diagram")
```




```
#### Come back to this
# how good's the fit?
mantel(nms2.xod~sppdata.xbcd,nboot=0)

# Get R2 for NMS ordinations ...
# You have to do this by differencing for NMS, cuz
# the axes are computed simultaneously:
# Get OD for 1 AND 2 AND 3 axes (NOT axis 1 OR 2 OR 3).
# axis 1 is OK as is
# (note this is a Mantel correlation, but done as a
# Pearson correlation cuz we don't care about the P-value):
nms.od1 <- dist(spp.nms.pca_scores[,1])
nms.od2 <- dist(spp.nms.pca_scores[,1:2])
nms.od3 <- dist(spp.nms.pca_scores[,1:3])
nms.od4 <- dist(spp.nms.pca_scores[,1:4])
nms.od5 <- dist(spp.nms.pca_scores[,1:5])

# axis 1 is OK as is:
r1<-cor(sppdata.xbcd,nms.od1)
r2.1<-r1^2; r2.1
# axis 2 is 2-D minus 1-D solution:
r2<-cor(sppdata.xbcd,nms.od2)
r2.2<-r2^2; r2.2-r2.1; r2.2

r3<-cor(sppdata.xbcd,nms.od3)
r2.3<-r3^2; r2.3-r2.2-r2.1; r2.3

r4<-cor(sppdata.xbcd,nms.od4)
r2.4<-r4^2; r2.4-r2.3-r2.2-r2.1; r2.4
```

```
r5<-cor(sppdata.xbcd,nms.od5)
r2.5<-r5^2; r2.5-r2.4-r2.3-r2.2-r2.1; r2.5

# then back to VEGAN for wgt'd avg scores for the species
# (note, VEGAN functions are still attached):

## Plot most extreme species WAs with environmental variable biplots per Axis
library(vegan)
## Compute WAs, write to table
spp.wa <- wascores(spp.nms.pca_scores,sppdata[,-1:-4])
spp.wa.table<-as.matrix(spp.wa)
write.csv(spp.wa.table, "spp_wa_table4115.csv")

## Load WAs of interest
NMS1sppnames<-as.matrix(read.csv("NMS1.csv", header=TRUE))
NMS2sppnames<-as.matrix(read.csv("NMS2.csv", header=TRUE))
class(NMS1sppnames)

## Generate jpegs of plots
jpeg("PlainNMS.jpg")
jpeg("SppEnvNMS1.jpg")
jpeg("SppEnvNMS2.jpg")
dev.off()

# plot axes 1 & 2, with NMS2 being the vertical axis:
# big points
plot(spp.nms.pca_scores[,1:2],pch=19, col="grey", xlab="NMS 1",ylab="NMS 2")
# small points
plot(spp.nms.pca_scores[,1:2],pch=19, cex=0.5,col="grey", xlab="NMS 1",ylab="NMS 2")
```



```
## to write a legend for all veg plots
colors<-c("grey")
pts<-c("Vegetation sample plots")
legend("bottomleft",legend=pts,text.col=colors,bty="n",cex=1.1)

## large points of WA spp names
points(NMS1sppnames[1:2,2:3],pch="+",lwd=2, cex=1.4,col="red")
text(NMS1sppnames[1:2,2:3],NMS1sppnames[1:2,1],cex=1.4,col="red", pos=2)
points(NMS1sppnames[3:4,2:3],pch="+",lwd=2, cex=1.4,col="red")
text(NMS1sppnames[3:4,2:3],NMS1sppnames[3:4,1],cex=1.4,col="red", pos=2)
points(NMS2sppnames[,2:3],pch="+",lwd=2, cex=1.4,col="red")
text(NMS2sppnames[,2:3],NMS2sppnames[,1],cex=1.4,col="red", pos=1)

## smaller points of WA spp names
points(NMS1sppnames[1:2,2:3],pch="+",lwd=2, cex=.75,col="blue")
text(NMS1sppnames[1:2,2:3],NMS1sppnames[1:2,1],cex=.75,col="blue", pos=4)
points(NMS1sppnames[3:4,2:3],pch="+",lwd=2, cex=.75,col="blue")
text(NMS1sppnames[3:4,2:3],NMS1sppnames[3:4,1],cex=.75,col="blue", pos=2)
points(NMS2sppnames[,2:3],pch="+",lwd=2, cex=.75,col="red")
text(NMS2sppnames[,2:3],NMS2sppnames[,1],cex=.75,col="red", pos=1)

## write legend for WAs
colors<-c("black","blue", "red")
axes<-c("Species most correlated with:", "NMS Axis 1", "NMS Axis 2")
legend("bottomleft",legend=axes,text.col=colors,bty="n",cex=.75)
dev.off()

# if these plot the + and labels on top of each other, simple skip the
# call to points and plot the labels instead

# Correlate ordination axes with ENV:
spp.nms.env<-cor2m(spp.nms.pca_scores,envvars1[,-1:-2])
spp.nms.env.table<-as.matrix(spp.nms.env)
spp.nms.env.table
write.csv(spp.nms.env.table, "spp_nms_env2.csv")

# Flip axis 1, if you need to for cosmetic reasons:
# spp11.nms[,1] <- spp11.nms[,1]* -1.0

# Correlation vectors with ENV:
spp.nms.vf1<-vf(spp.nms.pca_scores[,1:2],envvars1[,-1:-2])
spp.nms.vf2<-vf(spp.nms.pca_scores[,1:2],envvars2[,-1:-2])
#spp.nms.vf3<-vf(spp.nms.pca_scores[,1:2],envvars3[,-1:-2])
#?vf
#class(spp.nms.vf)
#write.csv(spp.nms.vf, "spp_nms_vf.csv")
#env.vf<-vf(read.csv("spp_nms_vf.csv",header=TRUE))

# Plot env vars vectors
plot(spp.nms.pca_scores[,1:2],pch=19, cex=0.5,col="grey", xlab="NMS 1",ylab="NMS 2")
plot.vf(spp.nms.vf1, pval=0.05, col="darkblue", lwd=2, length=0.067,pos=4,cex=1.6)
plot.vf(spp.nms.vf2, pval=0.05, col="darkblue", lwd=2, length=0.067,pos=4,cex=1.6)
plot.vf(spp.nms.vf3, pval=0.05, col="darkblue", lwd=2, length=0.067,pos=4,cex=1.2)
colors<-c("darkblue")
axes<-c("Correlation vectors for environmental variables")
```

```
legend("topleft",legend=axes,text.col=colors,bty="n",cex=1.1)
dev.off()
plot.vf
# (length specifies the size of the arrowheads, in inches)

###########################################
####### CHANGE VECTORING ###############
###########################################

# the data we need for change vectors ...    # spp39.nms2 <- nms2.pca$scores
# what's in columns 1 and 2? i'm guessing that he's binding plot names and years to spp scores
#sppdata.plotinfo <- read.csv("DATA_AllInfo.csv")
plotinfo<-read.csv("DATA_PlotInfo_NoRare.csv")
names(plotinfo)
colnames(spp.nms.pca_scores)
plots.spp.nms <- data.frame(cbind(plotinfo[,1:2], spp.nms.pca_scores[,1:2], plotinfo[,6],plotinfo[,3:5]))
colnames(plots.spp.nms) <- c("plot", "year", "NMS1", "NMS2", "plot_class","BurnYear","TotBurns","TotSamp")
unique(plots.spp.nms$BurnYear)
unique(plots.spp.nms$TotBurns)
unique(plots.spp.nms$TotSamp)
Burn2x<-plots.spp.nms[which(plots.spp.nms$TotBurns=='2'),]
Burn1x<-plots.spp.nms[which(plots.spp.nms$TotBurns=='1'),]
Burn0x<-plots.spp.nms[which(plots.spp.nms$TotBurns=='0'),]

# Group plots by ecosystem type
# Interesting plots to follow these...
plots.spp.nms$plot_class
ecotypes<-unique(plots.spp.nms$plot_class)
ecotypes
plots.ecotypes<-subset(spp.nms.pca_scores,by=list(Ecotypes=plots.spp.nms$plot_class))

RichCove<-plots.spp.nms[which(plots.spp.nms$plot_class=='Rich Cove and Slope Forests'),]
colnames(RichCove)
unique(RichCove$plot_class)
unique(RichCove$year)
unique(RichCove$plot)
length(unique(RichCove$plot))  #length = 9
unique(RichCove$plot[RichCove$year==1992])
unique(RichCove$plot[RichCove$year==2010])
unique(RichCove$plot[RichCove$year==2011])
nrow(RichCove)

RockOut<-plots.spp.nms[which(plots.spp.nms$plot_class=='Rock Outcrops'),]
colnames(RockOut)
unique(RockOut$plot_class)
unique(RockOut$year)
unique(RockOut$plot)
length(unique(RockOut$plot)) #length = 11
unique(RockOut$plot[RockOut$year==1992])
unique(RockOut$plot[RockOut$year==2011])
unique(RockOut$plot[RockOut$year==2014])
nrow(RockOut)

RockyStream<-plots.spp.nms[which(plots.spp.nms$plot_class=='Rocky Streamside Shrublands'),]
colnames(RockyStream)
```

```
unique(RockyStream$plot_class)
unique(RockyStream$year)
unique(RockyStream$plot)
length(unique(RockyStream$plot)) #length = 2
unique(RockyStream$plot[RockyStream$year==1992])
nrow(RockyStream)

Alluvial<-plots.spp.nms[which(plots.spp.nms$plot_class=='Alluvial Forests'),]
colnames(Alluvial)
unique(Alluvial$plot_class)
unique(Alluvial$year)
unique(Alluvial$plot)
length(unique(Alluvial$plot)) #length = 3
unique(Alluvial$plot[Alluvial$year==1992])
unique(Alluvial$plot[Alluvial$year==2010])
unique(Alluvial$plot[Alluvial$year==2011])
nrow(Alluvial)

source("change_vector_edits.R")
source("change_vectorx.R")
source("group.cv.R")

########################
#### ACID COVE ####
########################
AcidCove<-plots.spp.nms[which(plots.spp.nms$plot_class=='Acid Cove and Slope Forests'),]
colnames(AcidCove)
unique(AcidCove$plot_class)
unique(AcidCove$year)
unique(AcidCove$plot)
length(unique(AcidCove$plot))
unique(AcidCove$plot[AcidCove$year==1992])
unique(AcidCove$plot[AcidCove$year==2003])
unique(AcidCove$plot[AcidCove$year==2009])
unique(AcidCove$plot[AcidCove$year==2010])
unique(AcidCove$plot[AcidCove$year==2011])
unique(AcidCove$plot[AcidCove$year==2014])
nrow(AcidCove)

AcidCove1992<-AcidCove[which(AcidCove$year=='1992'),]
length(unique(AcidCove1992$plot))
AcidCove2003<-AcidCove[which(AcidCove$year=='2003'),]
length(unique(AcidCove2003$plot))
AcidCove2009<-AcidCove[which(AcidCove$year=='2009'),]
length(unique(AcidCove2009$plot))
AcidCove2010<-AcidCove[which(AcidCove$year=='2010'),]
length(unique(AcidCove2010$plot))
AcidCove2011<-AcidCove[which(AcidCove$year=='2011'),]
length(unique(AcidCove2011$plot))
AcidCove2014<-AcidCove[which(AcidCove$year=='2014'),]
length(unique(AcidCove2014$plot))

AcidCove2x<-AcidCove[which(AcidCove$TotBurns=='2'),]
AcidCove2x
AcidCove2xx<-unique(AcidCove2x$plot)
```

```
length(AcidCove2xx)
AcidCove1x<-AcidCove[which(AcidCove$TotBurns=='1'),]
AcidCove1xx<-unique(AcidCove1x$plot)
length(AcidCove1xx)
AcidCove0x<-AcidCove[which(AcidCove$TotBurns=='0'),]
AcidCove0xx<-unique(AcidCove0x$plot)
length(AcidCove0xx)
# plot axes 1 & 2, with NMS1 being the vertical axis:
jpeg('AcidCove2Burns.jpg')
plot(spp.nms.pca_scores[,1:2],pch=19, cex=.5, col= "grey", xlab="NMS 1",ylab="NMS 2")
points(AcidCove1992[,3:4], pch=19, col= "darkred")
points(AcidCove2003[,3:4], pch=19, col= "chocolate1")
points(AcidCove2009[,3:4], pch=19, col= "gold")
points(AcidCove2010[,3:4], pch=19, col= "green")
points(AcidCove2011[,3:4], pch=19, col= "blue")
points(AcidCove2014[,3:4], pch=19, col= "darkorchid1")
colors<-c("black","darkred","chocolate1","gold","green","blue","darkorchid1", "grey")
years<-c("Sample Years","1992  n=50","2003  n=7","2009  n=3","2010  n=17","2011  n=28","2014  n=11",
"Other Plots")
legend("topright",legend=years,text.col=colors,bty="n",cex=1)
colors2<-c("black", "mediumturquoise")
burnfreq<-c("Vectors", "Burned 0x  n=17" )
colors2<-c("black","darkgreen", "mediumturquoise")
burnfreq<-c("Vectors", "Burned 1x  n=22","Burned 0x  n=17")
colors2<-c("black", "deeppink","darkgreen", "mediumturquoise" )
burnfreq<-c("Vectors", "Burned 2x  n=11", "Burned 1x  n=22", "Burned 0x  n=17" )
legend("bottomleft", legend=burnfreq, text.col=colors2, bty="n", cex=1 )
dev.off()

? plot
# arguments are data, plot, color, linewidth:
# a group change vector ...
group.cv(plots.spp.nms,AcidCove2xx,color="deeppink",lwidth=3)
group.cv(plots.spp.nms,AcidCove1xx,color="darkgreen",lwidth=1)
group.cv(plots.spp.nms,AcidCove0xx,color="mediumturquoise",lwidth=1)
dev.off()

########################
#### XERIC EVERGREEN ####
########################
XericEv<-plots.spp.nms[which(plots.spp.nms$plot_class=='Xeric Evergreen Forests'),]
colnames(XericEv)
unique(XericEv$plot_class)
unique(XericEv$year)
unique(XericEv$plot)
length(unique(XericEv$plot))
unique(XericEv$plot[XericEv$year==1992])
unique(XericEv$plot[XericEv$year==2003])
unique(XericEv$plot[XericEv$year==2009])
unique(XericEv$plot[XericEv$year==2010])
unique(XericEv$plot[XericEv$year==2011])
unique(XericEv$plot[XericEv$year==2014])
nrow(XericEv)
```

```
XericEv1992<-XericEv[which(XericEv$year=='1992'),]
length(unique(XericEv1992$plot))
XericEv2003<-XericEv[which(XericEv$year=='2003'),]
length(unique(XericEv2003$plot))
XericEv2009<-XericEv[which(XericEv$year=='2009'),]
length(unique(XericEv2009$plot))
XericEv2010<-XericEv[which(XericEv$year=='2010'),]
length(unique(XericEv2010$plot))
XericEv2011<-XericEv[which(XericEv$year=='2011'),]
length(unique(XericEv2011$plot))
XericEv2014<-XericEv[which(XericEv$year=='2014'),]
length(unique(XericEv2014$plot))

XericEv2x<-XericEv[which(XericEv$TotBurns=='2'),]
XericEv2x
XericEv2xx<-unique(XericEv2x$plot)
length(XericEv2xx)
XericEv1x<-XericEv[which(XericEv$TotBurns=='1'),]
XericEv1xx<-unique(XericEv1x$plot)
length(XericEv1xx)
XericEv0x<-XericEv[which(XericEv$TotBurns=='0'),]
XericEv0xx<-unique(XericEv0x$plot)
length(XericEv0xx)
# plot axes 1 & 2, with NMS1 being the vertical axis:
plot(spp.nms.pca_scores[,1:2],pch=19, cex=.5, col= "grey", xlab="NMS 1",ylab="NMS 2", main="Xeric
Evergreen Forests Vectors: Burned 2x, 1x, and 0x")
points(XericEv1992[,3:4], pch=19, col= "darkred")
points(XericEv2003[,3:4], pch=19, col= "chocolate1")
points(XericEv2009[,3:4], pch=19, col= "gold")
points(XericEv2010[,3:4], pch=19, col= "green")
points(XericEv2011[,3:4], pch=19, col= "blue")
points(XericEv2014[,3:4], pch=19, col= "darkorchid1")
colors<-c("black","darkred","chocolate1","gold","green","blue","darkorchid1", "grey")
years<-c("Sample Years","1992  n=84","2003  n=18","2009  n=18","2010  n=43","2011  n=31","2014  n=4",
"Other Plots")
legend("topright",legend=years,text.col=colors,bty="n",cex=1)
colors2<-c("black", "deeppink","darkgreen", "mediumturquoise" )
burnfreq<-c("Vectors", "Burned 2x  n=46", "Burned 1x  n=16", "Burned 0x  n=22" )
legend("bottomleft", legend=burnfreq, text.col=colors2, bty="n", cex=1 )
? plot

# arguments are data, plot, color, linewidth:
# a group change vector ...
group.cv(plots.spp.nms,XericEv2xx,color="deeppink",lwidth=1)
group.cv(plots.spp.nms,XericEv1xx,color="darkgreen",lwidth=1)
group.cv(plots.spp.nms,XericEv0xx,color="mediumturquoise",lwidth=1)

#########################
#### MONTANE OAK ####
#########################
MontOak<-plots.spp.nms[which(plots.spp.nms$plot_class=='Montane Oak Forests'),]
colnames(MontOak)
unique(MontOak$plot_class)
unique(MontOak$year)
unique(MontOak$plot)
```

```
length(unique(MontOak$plot))
unique(MontOak$plot[MontOak$year==1992])
unique(MontOak$plot[MontOak$year==2003])
unique(MontOak$plot[MontOak$year==2009])
unique(MontOak$plot[MontOak$year==2010])
unique(MontOak$plot[MontOak$year==2011])
unique(MontOak$plot[MontOak$year==2014])
nrow(MontOak)

MontOak1992<-MontOak[which(MontOak$year=='1992'),]
length(unique(MontOak1992$plot))
MontOak2003<-MontOak[which(MontOak$year=='2003'),]
length(unique(MontOak2003$plot))
MontOak2009<-MontOak[which(MontOak$year=='2009'),]
length(unique(MontOak2009$plot))
MontOak2010<-MontOak[which(MontOak$year=='2010'),]
length(unique(MontOak2010$plot))
MontOak2011<-MontOak[which(MontOak$year=='2011'),]
length(unique(MontOak2011$plot))
MontOak2014<-MontOak[which(MontOak$year=='2014'),]
length(unique(MontOak2014$plot))

MontOak2x<-MontOak[which(MontOak$TotBurns=='2'),]
MontOak2x
MontOak2xx<-unique(MontOak2x$plot)
length(MontOak2xx)
MontOak1x<-MontOak[which(MontOak$TotBurns=='1'),]
MontOak1xx<-unique(MontOak1x$plot)
length(MontOak1xx)
MontOak0x<-MontOak[which(MontOak$TotBurns=='0'),]
MontOak0xx<-unique(MontOak0x$plot)
length(MontOak0xx)
# plot axes 1 & 2, with NMS1 being the vertical axis:
plot(spp.nms.pca_scores[,1:2],pch=19, cex=.5, col= "grey", xlab="NMS 1",ylab="NMS 2", main="Montane Oak
Forests Vectors: Burned 2x, 1x, and 0x")
points(MontOak1992[,3:4], pch=19, col= "darkred")
points(MontOak2003[,3:4], pch=19, col= "chocolate1")
points(MontOak2009[,3:4], pch=19, col= "gold")
points(MontOak2010[,3:4], pch=19, col= "green")
points(MontOak2011[,3:4], pch=19, col= "blue")
points(MontOak2014[,3:4], pch=19, col= "darkorchid1")
colors<-c("black","darkred","chocolate1","gold","green","blue","darkorchid1", "grey")
years<-c("Sample Years","1992  n=17","2003  n=0","2009  n=1","2010  n=5","2011  n=9","2014  n=3", "Other
Plots")
legend("topright",legend=years,text.col=colors,bty="n",cex=1)
colors2<-c("black", "deeppink","darkgreen", "mediumturquoise" )
burnfreq<-c("Vectors", "Burned 2x  n=9", "Burned 1x  n=8", "Burned 0x  n=0" )
legend("bottomleft", legend=burnfreq, text.col=colors2, bty="n", cex=1 )
? plot

# arguments are data, plot, color, linewidth:
# a group change vector ...
group.cv(plots.spp.nms,MontOak2xx,color="deeppink",lwidth=1)
group.cv(plots.spp.nms,MontOak1xx,color="darkgreen",lwidth=1)
group.cv(plots.spp.nms,MontOak0xx,color="mediumturquoise",lwidth=1)
```

```
#########################
#### Rich Cove and Slope Forests ####
#########################

RichCove<-plots.spp.nms[which(plots.spp.nms$plot_class=='Rich Cove and Slope Forests'),]
colnames(RichCove)
unique(RichCove$plot_class)
unique(RichCove$year)
unique(RichCove$plot)
length(unique(RichCove$plot))
unique(RichCove$plot[RichCove$year==1992])
unique(RichCove$plot[RichCove$year==2003])
unique(RichCove$plot[RichCove$year==2009])
unique(RichCove$plot[RichCove$year==2010])
unique(RichCove$plot[RichCove$year==2011])
unique(RichCove$plot[RichCove$year==2014])
nrow(RichCove)

RichCove1992<-RichCove[which(RichCove$year=='1992'),]
length(unique(RichCove1992$plot))
RichCove2003<-RichCove[which(RichCove$year=='2003'),]
length(unique(RichCove2003$plot))
RichCove2009<-RichCove[which(RichCove$year=='2009'),]
length(unique(RichCove2009$plot))
RichCove2010<-RichCove[which(RichCove$year=='2010'),]
length(unique(RichCove2010$plot))
RichCove2011<-RichCove[which(RichCove$year=='2011'),]
length(unique(RichCove2011$plot))
RichCove2014<-RichCove[which(RichCove$year=='2014'),]
length(unique(RichCove2014$plot))

RichCove2x<-RichCove[which(RichCove$TotBurns=='2'),]
RichCove2x
RichCove2xx<-unique(RichCove2x$plot)
length(RichCove2xx)
RichCove1x<-RichCove[which(RichCove$TotBurns=='1'),]
RichCove1xx<-unique(RichCove1x$plot)
length(RichCove1xx)
RichCove0x<-RichCove[which(RichCove$TotBurns=='0'),]
RichCove0xx<-unique(RichCove0x$plot)
length(RichCove0xx)
# plot axes 1 & 2, with NMS1 being the vertical axis:
plot(spp.nms.pca_scores[,1:2],pch=19, cex=.5, col= "grey", xlab="NMS 1",ylab="NMS 2", main="Rich Cove and
Slope Forests Vectors: Burned 2x, 1x, and 0x")
points(RichCove1992[,3:4], pch=19, col= "darkred")
points(RichCove2003[,3:4], pch=19, col= "chocolate1")
points(RichCove2009[,3:4], pch=19, col= "gold")
points(RichCove2010[,3:4], pch=19, col= "green")
points(RichCove2011[,3:4], pch=19, col= "blue")
points(RichCove2014[,3:4], pch=19, col= "darkorchid1")
colors<-c("black","darkred","chocolate1","gold","green","blue","darkorchid1", "grey")
years<-c("Sample Years","1992  n=9","2003  n=0","2009  n=0","2010  n=2","2011  n=6","2014  n=0", "Other
Plots")
legend("topright",legend=years,text.col=colors,bty="n",cex=1)
```

```
colors2<-c("black", "deeppink","darkgreen", "mediumturquoise" )
burnfreq<-c("Vectors", "Burned 2x  n=1", "Burned 1x  n=3", "Burned 0x  n=5" )
legend("bottomleft", legend=burnfreq, text.col=colors2, bty="n", cex=1 )

# arguments are data, plot, color, linewidth:
# a group change vector ...
group.cv(plots.spp.nms,RichCove2xx,color="deeppink",lwidth=1)
group.cv(plots.spp.nms,RichCove1xx,color="darkgreen",lwidth=1)
group.cv(plots.spp.nms,RichCove0xx,color="mediumturquoise",lwidth=1)


#########################
#### Alluvial Forests ####
#########################

Alluvial<-plots.spp.nms[which(plots.spp.nms$plot_class=='Alluvial Forests'),]
colnames(Alluvial)
unique(Alluvial$plot_class)
unique(Alluvial$year)
unique(Alluvial$plot)
length(unique(Alluvial$plot))
unique(Alluvial$plot[Alluvial$year==1992])
unique(Alluvial$plot[Alluvial$year==2003])
unique(Alluvial$plot[Alluvial$year==2009])
unique(Alluvial$plot[Alluvial$year==2010])
unique(Alluvial$plot[Alluvial$year==2011])
unique(Alluvial$plot[Alluvial$year==2014])
nrow(Alluvial)

Alluvial1992<-Alluvial[which(Alluvial$year=='1992'),]
length(unique(Alluvial1992$plot))
Alluvial2003<-Alluvial[which(Alluvial$year=='2003'),]
length(unique(Alluvial2003$plot))
Alluvial2009<-Alluvial[which(Alluvial$year=='2009'),]
length(unique(Alluvial2009$plot))
Alluvial2010<-Alluvial[which(Alluvial$year=='2010'),]
length(unique(Alluvial2010$plot))
Alluvial2011<-Alluvial[which(Alluvial$year=='2011'),]
length(unique(Alluvial2011$plot))
Alluvial2014<-Alluvial[which(Alluvial$year=='2014'),]
length(unique(Alluvial2014$plot))

Alluvial2x<-Alluvial[which(Alluvial$TotBurns=='2'),]
Alluvial2x
Alluvial2xx<-unique(Alluvial2x$plot)
length(Alluvial2xx)
Alluvial1x<-Alluvial[which(Alluvial$TotBurns=='1'),]
Alluvial1xx<-unique(Alluvial1x$plot)
length(Alluvial1xx)
Alluvial0x<-Alluvial[which(Alluvial$TotBurns=='0'),]
Alluvial0xx<-unique(Alluvial0x$plot)
length(Alluvial0xx)
# plot axes 1 & 2, with NMS1 being the vertical axis:
plot(spp.nms.pca_scores[,1:2],pch=19, cex=.5, col= "grey", xlab="NMS 1",ylab="NMS 2", main="Alluvial
Forests Vectors: Burned 2x, 1x, and 0x")
```

```
points(Alluvial1992[,3:4], pch=19, col= "darkred")
points(Alluvial2003[,3:4], pch=19, col= "chocolate1")
points(Alluvial2009[,3:4], pch=19, col= "gold")
points(Alluvial2010[,3:4], pch=19, col= "green")
points(Alluvial2011[,3:4], pch=19, col= "blue")
points(Alluvial2014[,3:4], pch=19, col= "darkorchid1")
colors<-c("black","darkred","chocolate1","gold","green","blue","darkorchid1", "grey")
years<-c("Sample Years","1992  n=3","2003  n=0","2009  n=0","2010  n=1","2011  n=1","2014  n=0", "Other
Plots")
legend("topright",legend=years,text.col=colors,bty="n",cex=1)
colors2<-c("black", "deeppink","darkgreen", "mediumturquoise" )
burnfreq<-c("Vectors", "Burned 2x  n=0", "Burned 1x  n=1", "Burned 0x  n=2" )
legend("bottomleft", legend=burnfreq, text.col=colors2, bty="n", cex=1 )

# arguments are data, plot, color, linewidth:
# a group change vector ...
group.cv(plots.spp.nms,Alluvial2xx,color="deeppink",lwidth=1)
group.cv(plots.spp.nms,Alluvial1xx,color="darkgreen",lwidth=1)
group.cv(plots.spp.nms,Alluvial0xx,color="mediumturquoise",lwidth=1)

########################
#### Rock Outcrops ####
########################

RockOut<-plots.spp.nms[which(plots.spp.nms$plot_class=='Rock Outcrops'),]
colnames(RockOut)
unique(RockOut$plot_class)
unique(RockOut$year)
unique(RockOut$plot)
length(unique(RockOut$plot))
unique(RockOut$plot[RockOut$year==1992])
unique(RockOut$plot[RockOut$year==2003])
unique(RockOut$plot[RockOut$year==2009])
unique(RockOut$plot[RockOut$year==2010])
unique(RockOut$plot[RockOut$year==2011])
unique(RockOut$plot[RockOut$year==2014])
nrow(RockOut)

RockOut1992<-RockOut[which(RockOut$year=='1992'),]
length(unique(RockOut1992$plot))
RockOut2003<-RockOut[which(RockOut$year=='2003'),]
length(unique(RockOut2003$plot))
RockOut2009<-RockOut[which(RockOut$year=='2009'),]
length(unique(RockOut2009$plot))
RockOut2010<-RockOut[which(RockOut$year=='2010'),]
length(unique(RockOut2010$plot))
RockOut2011<-RockOut[which(RockOut$year=='2011'),]
length(unique(RockOut2011$plot))
RockOut2014<-RockOut[which(RockOut$year=='2014'),]
length(unique(RockOut2014$plot))

RockOut2x<-RockOut[which(RockOut$TotBurns=='2'),]
RockOut2x
RockOut2xx<-unique(RockOut2x$plot)
length(RockOut2xx)
```

```
RockOut1x<-RockOut[which(RockOut$TotBurns=='1'),]
RockOut1xx<-unique(RockOut1x$plot)
length(RockOut1xx)
RockOut0x<-RockOut[which(RockOut$TotBurns=='0'),]
RockOut0xx<-unique(RockOut0x$plot)
length(RockOut0xx)
# plot axes 1 & 2, with NMS1 being the vertical axis:
plot(spp.nms.pca_scores[,1:2],pch=19, cex=.5, col= "grey", xlab="NMS 1",ylab="NMS 2", main="Rock Outcrops
Vectors: Burned 2x, 1x, and 0x")
points(RockOut1992[,3:4], pch=19, col= "darkred")
points(RockOut2003[,3:4], pch=19, col= "chocolate1")
points(RockOut2009[,3:4], pch=19, col= "gold")
points(RockOut2010[,3:4], pch=19, col= "green")
points(RockOut2011[,3:4], pch=19, col= "blue")
points(RockOut2014[,3:4], pch=19, col= "darkorchid1")
colors<-c("black","darkred","chocolate1","gold","green","blue","darkorchid1", "grey")
years<-c("Sample Years","1992  n=10","2003  n=0","2009  n=0","2010  n=0", "2011  n=7","2014  n=3", "Other
Plots")
legend("topright",legend=years,text.col=colors,bty="n",cex=1)
colors2<-c("black", "deeppink","darkgreen", "mediumturquoise" )
burnfreq<-c("Vectors", "Burned 2x  n=6", "Burned 1x  n=0", "Burned 0x  n=3" )
legend("bottomleft", legend=burnfreq, text.col=colors2, bty="n", cex=1 )

# arguments are data, plot, color, linewidth:
# a group change vector ...
group.cv(plots.spp.nms,RockOut2xx,color="deeppink",lwidth=1)
group.cv(plots.spp.nms,RockOut1xx,color="darkgreen",lwidth=1)
group.cv(plots.spp.nms,RockOut0xx,color="mediumturquoise",lwidth=1)

########################
#### Rocky Streamside Shrublands ####
#########################

RockyStream<-plots.spp.nms[which(plots.spp.nms$plot_class=='Rocky Streamside Shrublands'),]
colnames(RockyStream)
unique(RockyStream$plot_class)
unique(RockyStream$year)
unique(RockyStream$plot)
length(unique(RockyStream$plot))
unique(RockyStream$plot[RockyStream$year==1992])
unique(RockyStream$plot[RockyStream$year==2003])
unique(RockyStream$plot[RockyStream$year==2009])
unique(RockyStream$plot[RockyStream$year==2010])
unique(RockyStream$plot[RockyStream$year==2011])
unique(RockyStream$plot[RockyStream$year==2014])
nrow(RockyStream)

RockyStream1992<-RockyStream[which(RockyStream$year=='1992'),]
length(unique(RockyStream1992$plot))
RockyStream2003<-RockyStream[which(RockyStream$year=='2003'),]
length(unique(RockyStream2003$plot))
RockyStream2009<-RockyStream[which(RockyStream$year=='2009'),]
length(unique(RockyStream2009$plot))
RockyStream2010<-RockyStream[which(RockyStream$year=='2010'),]
length(unique(RockyStream2010$plot))
```

```
RockyStream2011<-RockyStream[which(RockyStream$year=='2011'),]
length(unique(RockyStream2011$plot))
RockyStream2014<-RockyStream[which(RockyStream$year=='2014'),]
length(unique(RockyStream2014$plot))

RockyStream2x<-RockyStream[which(RockyStream$TotBurns=='2'),]
RockyStream2x
RockyStream2xx<-unique(RockyStream2x$plot)
length(RockyStream2xx)
RockyStream1x<-RockyStream[which(RockyStream$TotBurns=='1'),]
RockyStream1xx<-unique(RockyStream1x$plot)
length(RockyStream1xx)
RockyStream0x<-RockyStream[which(RockyStream$TotBurns=='0'),]
RockyStream0xx<-unique(RockyStream0x$plot)
length(RockyStream0xx)
# plot axes 1 & 2, with NMS1 being the vertical axis:
plot(spp.nms.pca_scores[,1:2],pch=19, cex=.5, col= "grey", xlab="NMS 1",ylab="NMS 2", main="Rocky
Streamside Shrublands Vectors: Burned 2x, 1x, and 0x")
points(RockyStream1992[,3:4], pch=19, col= "darkred")
points(RockyStream2003[,3:4], pch=19, col= "chocolate1")
points(RockyStream2009[,3:4], pch=19, col= "gold")
points(RockyStream2010[,3:4], pch=19, col= "green")
points(RockyStream2011[,3:4], pch=19, col= "blue")
points(RockyStream2014[,3:4], pch=19, col= "darkorchid1")
colors<-c("black","darkred","chocolate1","gold","green","blue","darkorchid1", "grey")
years<-c("Sample Years","1992  n=2","2003  n=0","2009  n=0","2010  n=0", "2011  n=0","2014  n=0", "Other
Plots")
legend("topright",legend=years,text.col=colors,bty="n",cex=1)
colors2<-c("black", "deeppink","darkgreen", "mediumturquoise" )
burnfreq<-c("Vectors", "Burned 2x  n=0", "Burned 1x  n=0", "Burned 0x  n=2" )
legend("bottomleft", legend=burnfreq, text.col=colors2, bty="n", cex=1 )

# arguments are data, plot, color, linewidth:
# a group change vector ...
group.cv(plots.spp.nms,RockyStream2xx,color="deeppink",lwidth=1)
group.cv(plots.spp.nms,RockyStream1xx,color="darkgreen",lwidth=1)
group.cv(plots.spp.nms,RockyStream0xx,color="mediumturquoise",lwidth=1)
```

Restoration Goals Analyses

Ericaceous Species

```
# perform t-tests to determine before-after changes in density, IVs of key species

# 1) test ericaceous shrubs for changes from 1992 to each timestep, separated by # of burns
# 2) test ericaceous shrubs for changes from 1992 to each timestep, separated by fire instance (before-after fire); does effect last?

setwd("~/Desktop/DataAnalysis")
data <- read.csv("DATA_NoRare_ttests.csv")
density.data<-read.csv("Density.csv")
under.dens.data<-read.csv("UnderRelDens.csv")
under.ba.data<-read.csv("UnderRelBA.csv")
under.iv.data<-read.csv("UnderstoryIV.csv")
names(data)

### install necessary packages ###
# if you want to pivot plot numbers to be column headers, use cast(data, desired row header ~ desired column header)
install.packages('reshape')
library('reshape')
install.packages('car')
library('car')
library('Matrix')
install.packages('multicomp')
detach(package:reshape, unload=T)
detach(package:car, unload=T)
detach(package:multicomp, unload=T)

##################################################
####Count burns by sample year
##################################################
## Count burns for plots by sample year ##
AllTypes2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
AllTypes2x03<-AllTypes2x[which(AllTypes2x$year=='2003'),]
AllTypes2x03$plot
AllTypes1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
AllTypes1x03<-AllTypes1x[which(AllTypes1x$year=='2003'),]
AllTypes1x03$plot
AllTypes0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
AllTypes0x03<-AllTypes0x[which(AllTypes0x$year=='2003'),]
AllTypes0x03$plot

AllTypes2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
AllTypes2x09<-AllTypes2x[which(AllTypes2x$year=='2009'),]
AllTypes2x09$plot
AllTypes1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
AllTypes1x09<-AllTypes1x[which(AllTypes1x$year=='2009'),]
AllTypes1x09$plot
AllTypes0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
AllTypes0x09<-AllTypes0x[which(AllTypes0x$year=='2009'),]
AllTypes0x09$plot
```

```
AllTypes2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
AllTypes2x10<-AllTypes2x[which(AllTypes2x$year=='2010'),]
AllTypes2x10$plot
AllTypes1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
AllTypes1x10<-AllTypes1x[which(AllTypes1x$year=='2010'),]
AllTypes1x10$plot
AllTypes0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
AllTypes0x10<-AllTypes0x[which(AllTypes0x$year=='2010'),]
AllTypes0x10$plot

AllTypes2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
AllTypes2x11<-AllTypes2x[which(AllTypes2x$year=='2011'),]
AllTypes2x11$plot
AllTypes1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
AllTypes1x11<-AllTypes1x[which(AllTypes1x$year=='2011'),]
AllTypes1x11$plot
AllTypes0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
AllTypes0x11<-AllTypes0x[which(AllTypes0x$year=='2011'),]
AllTypes0x11$plot

AllTypes2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
AllTypes2x14<-AllTypes2x[which(AllTypes2x$year=='2014'),]
AllTypes2x14$plot
AllTypes1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
AllTypes1x14<-AllTypes1x[which(AllTypes1x$year=='2014'),]
AllTypes1x14$plot
AllTypes0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
AllTypes0x14<-AllTypes0x[which(AllTypes0x$year=='2014'),]
AllTypes0x14$plot

#####################################################
################ ERICACEOUS SPP ####################
#####################################################

### isolate ericaceous shrubs ###
eric.shrubs.matrix<-as.matrix(cbind(data[,44],data[,81],data[,83],data[,85:86],data[,108:111]))
#colnames(eric.shrubs)<-c("kalmlat", "rhodcat","rhodmax", "rhodmin", "rhodper",
"vacccor","vaccpal","vaccsim","vaccsta")
eric.shrubs.rs<-rowSums(eric.shrubs.matrix)
eric.shrubs<-data.frame(eric.shrubs.rs)
eric.shrubs

### bind to plot information ###
data2<-data.frame(cbind(data[,1:8],eric.shrubs))
data2
colnames(data2)<-c("plot", "year", "Burn2000","Burn2007","Burn2013", "TotBurns", "TotSamp", "plot_class",
"eric_shrubs")
names(data2)
data2$eric_shrubs
data2$Burn2000
data2$year==2014

AllTypes<-data2
length(unique(AllTypes$plot[AllTypes$year=='1992']))
```

```
length(unique(AllTypes$plot[AllTypes$year=='2003']))
length(unique(AllTypes$plot[AllTypes$year=='2009']))
length(unique(AllTypes$plot[AllTypes$year=='2010']))
length(unique(AllTypes$plot[AllTypes$year=='2011']))
length(unique(AllTypes$plot[AllTypes$year=='2014']))

### rbind Mont Oak, Xeric Ev, and Acid Cove to make "All Types" ###
#MontOak<-data2[which(data2$plot_class=='Montane Oak Forests'),]
#AcidCove<-data2[which(data2$plot_class=='Acid Cove and Slope Forests'),]
#XericEv<-data2[which(data2$plot_class=='Xeric Evergreen Forests'),]

#AllTypes<-rbind(AcidCove,MontOak,XericEv)
#names(AllTypes)

### Isolating burn number and year ###
Burn2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
names(Burn2x)
Burn2x$plot
Burn1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
names(Burn1x)
Burn1x$plot
Burn0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
names(Burn0x)
(unique(Burn0x$year))
Burn0x$plot

length(unique(Burn0x$plot[Burn0x$year>2004]))
length(unique(Burn0x$plot[Burn0x$year==2003]))

Burn1x$Burn2000
Burn1x$Burn2007

AllTypes00only<-Burn1x[which(Burn1x$Burn2000=='1'),]
names(AllTypes00only)
length(unique(AllTypes00only$plot_class))
AllTypes00only$year
names(AllTypes00only)

AllTypes07only<-Burn1x[which(Burn1x$Burn2007=='1'),]
names(AllTypes07only)
length(unique(AllTypes07only$plot_class))
AllTypes07only$year

AllTypes13only<-Burn1x[which(Burn1x$Burn2013=='1'),]
names(AllTypes13only)
length(unique(AllTypes13only$plot_class))
AllTypes13only$year

AllTypes00.07<-Burn2x[which(Burn2x$Burn2007=='1'),]
names(AllTypes00.07)
length(unique(AllTypes00.07$plot[AllTypes00.07$year=='2003']))
AllTypes00.07$year
AllTypes00.13<-Burn2x[which(Burn2x$Burn2013=='1'),]
names(AllTypes00.13)
length(unique(AllTypes00.13$plot_class))
```

```
length(unique(AllTypes00.13$plot[AllTypes00.13$year=='2003']))
AllTypes00.07$year
AllTypes00.13$year

(unique(AllTypes00.13$plot[AllTypes00.13$year==2010]))
length(unique(AllTypes00.13$plot[AllTypes00.13$year==2014]))

### Unburned
jpeg("BoxUnburned.jpg")
ATdata<-data.frame(cbind(Burn0x[,1:2],Burn0x[,9]))
colnames(ATdata)<-c("plot","year","eric_shrubs")
boxplot(eric_shrubs~year, col="chartreuse4", ATdata)
dev.off()
reg1<-lm(eric_shrubs~year,  ATdata)
plot(reg1)
names(ATdata)
ATdata$year
length(unique(ATdata$plot[ATdata$year==2011]))
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010", "Y2011")
?rowMeans
AT.aov.1$Y2011
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2010_11")
summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)
AT.aov$Y2010_11

#1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)

### Burn 2000 only
#ATdata<-data.frame(cbind(AllTypes00only[,1:2],AllTypes00only[,9]))
#colnames(ATdata)<-c("plot","year","eric_shrubs")
#names(ATdata)
#ATdata$year
#length(unique(ATdata$plot))
#AT.aov.1<-data.frame(cast(ATdata, plot~year))
#colnames(AT.aov.1 )<-c("plot", "Y1992", "Y2003", "Y2009", "Y2010", "Y2011")
#AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
```

```
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
#AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
#AT.aov.3
#AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
#colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
#AT.aov$Y2009_11

#1992
#t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
#t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)

# 2003
#t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)

### combine 2000 only, with options for 2000 & 2007 and 2000 & 2013 burns
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.07,AllTypes00.13)
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.13)
AllTypes.All00<-(AllTypes00only)
names(AllTypes.All00)
length(unique(AllTypes.All00$plot))
ATdata<-data.frame(cbind(AllTypes.All00[,1:2],AllTypes.All00[,9]))
colnames(ATdata)<-c("plot","year","eric_shrubs")
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,6]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2010_11","Y2014")
AT.aov$Y2009_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
### Burn 2007 only
ATdata<-data.frame(cbind(AllTypes07only[,1:2],AllTypes07only[,9]))
cols<-c("darkgreen", "darkgreen","orange","orange","orange","orange")
colnames(ATdata)<-c("plot","year","eric_shrubs")
boxplot(eric_shrubs~year, col=cols, ATdata)
```

```
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_10")
AT.aov$Y2009_10

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_10, alternative=c("greater"), paired=TRUE)

### Burn 2013 only
ATdata<-data.frame(cbind(AllTypes13only[,1:2],AllTypes13only[,9]))
jpeg("BoxBurned1x.jpg")
colnames(ATdata)<-c("plot","year","eric_shrubs")
cols<-c("chartreuse4", "chartreuse4","chartreuse4","orange")
boxplot(eric_shrubs~year, col=cols, ATdata)
dev.off()
length(unique(ATdata$plot[ATdata$year==2014]))
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,3:4]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:2],AT.aov.3[,1],AT.aov.1[,5]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2010_11", "Y2014")

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)
```

```
# 1992
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
# 2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)

### Burn 2000 and 2007
jpeg("Box2xBurned.jpg")
ATdata<-data.frame(cbind(AllTypes00.07[,1:2],AllTypes00.07[,9]))
colnames(ATdata)<-c("plot","year","eric_shrubs")
cols<-c("chartreuse4", "orange","darkred","darkred","darkred","darkred")
boxplot(eric_shrubs~year, col=cols, ATdata)
dev.off()
length(unique(ATdata$plot[ATdata$year==2011]))
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010", "Y2011")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
AT.aov$Y2009_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)

# Burn 2000 and 2013
ATdata<-data.frame(cbind(AllTypes00.13[,1:2],AllTypes00.13[,9]))
colnames(ATdata)<-c("plot","year","eric_shrubs")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010","Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
```

```
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,6]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003","Y2010_11", "Y2014")
AT.aov$Y2010_11
# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y2003, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
#2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)
```

Fire Intolerant Species

```
# perform t-tests to determine before-after changes in density, IVs of key species

# 1) test fire intolerant spp for changes from 1992 to each timestep, separated by # of burns
# 2) test fire intolerant spp for changes from 1992 to each timestep, separated by fire instance (before-after fire); does effect last?

setwd("~/Desktop/DataAnalysis")
data <- read.csv("DATA_NoRare_ttests.csv")
density.data<-read.csv("Density.csv")
under.dens.data<-read.csv("UnderRelDens.csv")
under.ba.data<-read.csv("UnderRelBA.csv")
under.iv.data<-read.csv("UnderstoryIV.csv")

### install necessary packages ###
# if you want to pivot plot numbers to be column headers, use cast(data, desired row header ~ desired column header)
install.packages('reshape')
library('reshape')
install.packages('car')
library('car')
library('Matrix')
install.packages('multicomp')
detach(package:reshape, unload=T)
detach(package:car, unload=T)
detach(package:multicomp, unload=T)
```

```
####################################################
################# FIRE INTOLERANT SPP ####################
####################################################

### isolate fire intolerant shrubs ###
fire.intolmatrix<-as.matrix(cbind(data[,11],data[,56],data[,65]))
# ACERRUB=11, OXYDARB=56, PINUSTR=66
fire.intol.rs<-rowSums(fire.intolmatrix)
fire.intol<-data.frame(fire.intol.rs)
fire.intol

### bind to plot information ###
data2<-data.frame(cbind(data[,1:8],fire.intol))
data2
colnames(data2)<-c("plot", "year", "Burn2000","Burn2007","Burn2013", "TotBurns", "TotSamp", "plot_class",
"fire_intol")
names(data2)
data2$fire_intol
data2$Burn2000

AllTypes<-data2
length(unique(AllTypes$plot[AllTypes$year=='1992']))
length(unique(AllTypes$plot[AllTypes$year=='2003']))
length(unique(AllTypes$plot[AllTypes$year=='2009']))
length(unique(AllTypes$plot[AllTypes$year=='2010']))
length(unique(AllTypes$plot[AllTypes$year=='2011']))
length(unique(AllTypes$plot[AllTypes$year=='2014']))

### rbind Mont Oak, Xeric Ev, and Acid Cove to make "All Types" ###
#MontOak<-data2[which(data2$plot_class=='Montane Oak Forests'),]
#AcidCove<-data2[which(data2$plot_class=='Acid Cove and Slope Forests'),]
#XericEv<-data2[which(data2$plot_class=='Xeric Evergreen Forests'),]
#AllTypes<-rbind(AcidCove,MontOak,XericEv)
#names(AllTypes)

### Isolating burn number and year ###
Burn2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
names(Burn2x)
Burn2x$plot
Burn1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
names(Burn1x)
Burn1x$plot
Burn0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
names(Burn0x)
(unique(Burn0x$year))
Burn0x$plot
Burn1x$Burn2000
Burn1x$Burn2007

AllTypes00only<-Burn1x[which(Burn1x$Burn2000=='1'),]
names(AllTypes00only)
length(unique(AllTypes00only$plot_class))
AllTypes00only$year
names(AllTypes00only)
```

```
AllTypes07only<-Burn1x[which(Burn1x$Burn2007=='1'),]
names(AllTypes07only)
length(unique(AllTypes07only$plot_class))
AllTypes07only$year

AllTypes13only<-Burn1x[which(Burn1x$Burn2013=='1'),]
names(AllTypes13only)
length(unique(AllTypes13only$plot_class))
AllTypes13only$year

AllTypes00.07<-Burn2x[which(Burn2x$Burn2007=='1'),]
names(AllTypes00.07)
length(unique(AllTypes00.07$plot[AllTypes00.07$year=='2003']))
AllTypes00.07$year

AllTypes00.13<-Burn2x[which(Burn2x$Burn2013=='1'),]
names(AllTypes00.13)
length(unique(AllTypes00.13$plot_class))
length(unique(AllTypes00.13$plot[AllTypes00.13$year=='2003']))
AllTypes00.07$year
AllTypes00.13$year

### Unburned
ATdata<-data.frame(cbind(Burn0x[,1:2],Burn0x[,9]))
colnames(ATdata)<-c("plot","year","fire_intol")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010", "Y2011")
?rowMeans
AT.aov.1$Y2011
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2010_11")
AT.aov$Y2010_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

#1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
```

```
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)

### Burn 2000 only
ATdata<-data.frame(cbind(AllTypes00only[,1:2],AllTypes00only[,9]))
colnames(ATdata)<-c("plot","year","fire_intol")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009", "Y2010", "Y2011")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
AT.aov$Y2009_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

#1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)

### combine 2000 only, with options for 2000 & 2007 and 2000 & 2013 burns
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.07,AllTypes00.13)
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.13)
names(AllTypes.All00)
length(unique(AllTypes.All00$plot))
ATdata<-data.frame(cbind(AllTypes.All00[,1:2],AllTypes.All00[,9]))
colnames(ATdata)<-c("plot","year","fire_intol")
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,7]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11","Y2014")
AT.aov$Y2009_11
```

```
summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y2003, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
#2009_11
t.test(AT.aov$Y2009_11, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)

### Burn 2007 only
ATdata<-data.frame(cbind(AllTypes07only[,1:2],AllTypes07only[,9]))
colnames(ATdata)<-c("plot","year","fire_intol")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_10")
AT.aov$Y2009_10

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_10, alternative=c("greater"), paired=TRUE)

### Burn 2013 only
ATdata<-data.frame(cbind(AllTypes13only[,1:2],AllTypes13only[,9]))
colnames(ATdata)<-c("plot","year","fire_intol")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,3:4]))
```

```
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:2],AT.aov.3[,1],AT.aov.1[,5]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2010_11", "Y2014")

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
# 2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)

### Burn 2000 and 2007
ATdata<-data.frame(cbind(AllTypes00.07[,1:2],AllTypes00.07[,9]))
colnames(ATdata)<-c("plot","year","fire_intol")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010", "Y2011")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
AT.aov$Y2009_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("greater"), paired=TRUE)
```

```
# Burn 2000 and 2013
ATdata<-data.frame(cbind(AllTypes00.13[,1:2],AllTypes00.13[,9]))
colnames(ATdata)<-c("plot","year","fire_intol")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010","Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,6]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003","Y2010_11", "Y2014")
AT.aov$Y2010_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("greater"), paired=TRUE)
t.test(AT.aov$Y2003, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
#2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("greater"), paired=TRUE)
```

Fire Dependent Species

```
# perform t-tests to determine before-after changes in density, IVs of key species

# 1) test ericaceous shrubs for changes from 1992 to each timestep, separated by # of burns
# 2) test ericaceous shrubs for changes from 1992 to each timestep, separated by fire instance (before-after fire); does effect last?
# 3) test fire-dependent species for increases in abundance; does effect last?

setwd("~/Desktop/DataAnalysis")
data <- read.csv("DATA_NoRare_ttests.csv")
density.data<-read.csv("Density.csv")
under.dens.data<-read.csv("UnderRelDens.csv")
under.ba.data<-read.csv("UnderRelBA.csv")
under.iv.data<-read.csv("UnderstoryIV.csv")
names(data)
```

```
### install necessary packages ###
# if you want to pivot plot numbers to be column headers, use cast(data, desired row header ~ desired
column header)
install.packages('reshape')
library('reshape')
install.packages('car')
library('car')
library('Matrix')
install.packages('multicomp')
detach(package:reshape, unload=T)
detach(package:car, unload=T)
detach(package:multicomp, unload=T)

####################################################
################ FIRE DEPENDENT SPP ###################
####################################################

### isolate fire spp ###
firespp.matrix<-as.matrix(cbind(data[,61],data[,63],data[,71], data[,73:74], data[,78]))
firespp.matrix
# 61=PINUPUN, 63=PINURIG, 71=QUERALB, 73=QUERCOC, 74=QUERMON, 78=QUERRUB
firespp.rs<-rowSums(firespp.matrix)
firespp<-data.frame(firespp.rs)
firespp

### bind to plot information ###
data2<-data.frame(cbind(data[,1:8],firespp))
data2
colnames(data2)<-c("plot", "year", "Burn2000","Burn2007","Burn2013", "TotBurns", "TotSamp", "plot_class",
"firespp")
names(data2)
data2$firespp
data2$Burn2000

AllTypes<-data2
length(unique(AllTypes$plot[AllTypes$year=='1992']))
length(unique(AllTypes$plot[AllTypes$year=='2003']))
length(unique(AllTypes$plot[AllTypes$year=='2009']))
length(unique(AllTypes$plot[AllTypes$year=='2010']))
length(unique(AllTypes$plot[AllTypes$year=='2011']))
length(unique(AllTypes$plot[AllTypes$year=='2014']))

### rbind Mont Oak, Xeric Ev, and Acid Cove to make "All Types" ###
#MontOak<-data2[which(data2$plot_class=='Montane Oak Forests'),]
#AcidCove<-data2[which(data2$plot_class=='Acid Cove and Slope Forests'),]
#XericEv<-data2[which(data2$plot_class=='Xeric Evergreen Forests'),]

#AllTypes<-rbind(AcidCove,MontOak,XericEv)
#names(AllTypes)

### Isolating burn number and year ###
Burn2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
names(Burn2x)
Burn2x$plot
Burn1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
```

```
names(Burn1x)
Burn1x$plot
Burn0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
names(Burn0x)
(unique(Burn0x$year))
Burn0x$plot

Burn1x$Burn2000
Burn1x$Burn2007

AllTypes00only<-Burn1x[which(Burn1x$Burn2000=='1'),]
names(AllTypes00only)
length(unique(AllTypes00only$plot_class))
AllTypes00only$year
names(AllTypes00only)

AllTypes07only<-Burn1x[which(Burn1x$Burn2007=='1'),]
names(AllTypes07only)
length(unique(AllTypes07only$plot_class))
AllTypes07only$year

AllTypes13only<-Burn1x[which(Burn1x$Burn2013=='1'),]
names(AllTypes13only)
length(unique(AllTypes13only$plot_class))
AllTypes13only$year

AllTypes00.07<-Burn2x[which(Burn2x$Burn2007=='1'),]
names(AllTypes00.07)
length(unique(AllTypes00.07$plot[AllTypes00.07$year=='2003']))
AllTypes00.07$year

AllTypes00.13<-Burn2x[which(Burn2x$Burn2013=='1'),]
names(AllTypes00.13)
length(unique(AllTypes00.13$plot_class))
length(unique(AllTypes00.13$plot[AllTypes00.13$year=='2003']))
AllTypes00.07$year
AllTypes00.13$year

### swap "less" and "less" to see if fire is reducing importance of fire spp

### Unburned
ATdata<-data.frame(cbind(Burn0x[,1:2],Burn0x[,9]))
colnames(ATdata)<-c("plot","year","firespp")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010", "Y2011")
?rowMeans
AT.aov.1$Y2011
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
```

```
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2010_11")
AT.aov$Y2010_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

#1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)

### Burn 2000 only
ATdata<-data.frame(cbind(AllTypes00only[,1:2],AllTypes00only[,9]))
colnames(ATdata)<-c("plot","year","firespp")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009", "Y2010", "Y2011")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
AT.aov$Y2009_11

#1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

### combine 2000 only, with options for 2000 & 2007 and 2000 & 2013 burns
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.07,AllTypes00.13)
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.13)
names(AllTypes.All00)
length(unique(AllTypes.All00$plot))
ATdata<-data.frame(cbind(AllTypes.All00[,1:2],AllTypes.All00[,9]))
colnames(ATdata)<-c("plot","year","firespp")
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
```

```
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,7]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11","Y2014")
AT.aov$Y2009_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y2003, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
#2009_11
t.test(AT.aov$Y2009_11, AT.aov$Y2014, alternative=c("less"), paired=TRUE)

### Burn 2007 only
ATdata<-data.frame(cbind(AllTypes07only[,1:2],AllTypes07only[,9]))
colnames(ATdata)<-c("plot","year","firespp")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_10")
AT.aov$Y2009_10

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)
```

```
# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_10, alternative=c("less"), paired=TRUE)

### Burn 2013 only
ATdata<-data.frame(cbind(AllTypes13only[,1:2],AllTypes13only[,9]))
colnames(ATdata)<-c("plot","year","firespp")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,3:4]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:2],AT.aov.3[,1],AT.aov.1[,5]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2010_11", "Y2014")

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
# 2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("less"), paired=TRUE)

### Burn 2000 and 2007
ATdata<-data.frame(cbind(AllTypes00.07[,1:2],AllTypes00.07[,9]))
colnames(ATdata)<-c("plot","year","firespp")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010", "Y2011")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
AT.aov$Y2009_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
```

```
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

# Burn 2000 and 2013
ATdata<-data.frame(cbind(AllTypes00.13[,1:2],AllTypes00.13[,9]))
colnames(ATdata)<-c("plot","year","firespp")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010","Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,6]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003","Y2010_11", "Y2014")
AT.aov$Y2010_11
#2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("less"), paired=TRUE)

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y2003, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
#2010_11
t.test(AT.aov$Y2009, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
```

Invasive Species

```
# perform t-tests to determine before-after changes in density, IVs of key species
# 1) test invasives for changes from 1992 to each timestep, separated by # of burns
# 2) test invasives for changes from 1992 to each timestep, separated by fire instance (before-after fire); does
effect last?
```

```
setwd("~/Desktop/DataAnalysis")
data <- read.csv("DATA_NoRare_ttests.csv")
density.data<-read.csv("Density.csv")
under.dens.data<-read.csv("UnderRelDens.csv")
under.ba.data<-read.csv("UnderRelBA.csv")
under.iv.data<-read.csv("UnderstoryIV.csv")

data.frame(names(data))

### install necessary packages ###
# if you want to pivot plot numbers to be column headers, use cast(data, desired row header ~ desired
column header)
install.packages('reshape')
library('reshape')
install.packages('car')
library('car')
library('Matrix')
install.packages('multicomp')
detach(package:reshape, unload=T)
detach(package:car, unload=T)
detach(package:multicomp, unload=T)

####################################################
################ Invasive SPP ####################
####################################################

### isolate invasive spp ###
invasive.matrix<-as.matrix(data[,59])
invasive.matrix
# 59 = PAULTOM
invasive.rs<-rowSums(invasive.matrix)
invasive<-data.frame(invasive.rs)
invasive

### bind to plot information ###
data2<-data.frame(cbind(data[,1:8],invasive))
data2
colnames(data2)<-c("plot", "year", "Burn2000","Burn2007","Burn2013", "TotBurns", "TotSamp", "plot_class",
"invasive")
names(data2)
data2$invasive
data2$Burn2000

AllTypes<-data2
length(unique(AllTypes$plot[AllTypes$year=='1992']))
length(unique(AllTypes$plot[AllTypes$year=='2003']))
length(unique(AllTypes$plot[AllTypes$year=='2009']))
length(unique(AllTypes$plot[AllTypes$year=='2010']))
length(unique(AllTypes$plot[AllTypes$year=='2011']))
length(unique(AllTypes$plot[AllTypes$year=='2014']))

### rbind Mont Oak, Xeric Ev, and Acid Cove to make "All Types" ###
#MontOak<-data2[which(data2$plot_class=='Montane Oak Forests'),]
#AcidCove<-data2[which(data2$plot_class=='Acid Cove and Slope Forests'),]
```

```
#XericEv<-data2[which(data2$plot_class=='Xeric Evergreen Forests'),]

#AllTypes<-rbind(AcidCove,MontOak,XericEv)
#names(AllTypes)

### Isolating burn number and year ###
Burn2x<-AllTypes[which(AllTypes$TotBurns=='2'),]
names(Burn2x)
Burn2x$plot
Burn1x<-AllTypes[which(AllTypes$TotBurns=='1'),]
names(Burn1x)
Burn1x$plot
Burn0x<-AllTypes[which(AllTypes$TotBurns=='0'),]
names(Burn0x)
(unique(Burn0x$year))
Burn0x$plot

Burn1x$Burn2000
Burn1x$Burn2007

AllTypes00only<-Burn1x[which(Burn1x$Burn2000=='1'),]
names(AllTypes00only)
length(unique(AllTypes00only$plot_class))
AllTypes00only$year
names(AllTypes00only)

AllTypes07only<-Burn1x[which(Burn1x$Burn2007=='1'),]
names(AllTypes07only)
length(unique(AllTypes07only$plot_class))
AllTypes07only$year

AllTypes13only<-Burn1x[which(Burn1x$Burn2013=='1'),]
names(AllTypes13only)
length(unique(AllTypes13only$plot_class))
AllTypes13only$year

AllTypes00.07<-Burn2x[which(Burn2x$Burn2007=='1'),]
names(AllTypes00.07)
length(unique(AllTypes00.07$plot[AllTypes00.07$year=='2003']))
AllTypes00.07$year

AllTypes00.13<-Burn2x[which(Burn2x$Burn2013=='1'),]
names(AllTypes00.13)
length(unique(AllTypes00.13$plot_class))
length(unique(AllTypes00.13$plot[AllTypes00.13$year=='2003']))
AllTypes00.07$year
AllTypes00.13$year

### swap "less" and "less" to see if fire is reducing importance of fire spp

### Unburned
ATdata<-data.frame(cbind(Burn0x[,1:2],Burn0x[,9]))
colnames(ATdata)<-c("plot","year","invasives")
names(ATdata)
ATdata$year
```

```
length(unique(ATdata$plot))
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010", "Y2011")
?rowMeans
AT.aov.1$Y2010
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2010_11")
AT.aov$Y2010_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

#1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)

### Burn 2000 only
#ATdata<-data.frame(cbind(AllTypes00only[,1:2],AllTypes00only[,9]))
#colnames(ATdata)<-c("plot","year","invasives")
#names(ATdata)
#ATdata$year
#length(unique(ATdata$plot))
#AT.aov.1<-data.frame(cast(ATdata, plot~year))
#colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009", "Y2010", "Y2011")
#AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
#AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
#AT.aov.3
#AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
#colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
#AT.aov$Y2009_11

#1992
#t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
#t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

# 2003
#t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)
```

```
### combine 2000 only, with options for 2000 & 2007 and 2000 & 2013 burns
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.07,AllTypes00.13)
AllTypes.All00<-rbind(AllTypes00only,AllTypes00.13)
names(AllTypes.All00)
length(unique(AllTypes.All00$plot))
ATdata<-data.frame(cbind(AllTypes.All00[,1:2],AllTypes.All00[,9]))
colnames(ATdata)<-c("plot","year","invasives")
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,7]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11","Y2014")
AT.aov$Y2009_11

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

### Burn 2007 only
ATdata<-data.frame(cbind(AllTypes07only[,1:2],AllTypes07only[,9]))
colnames(ATdata)<-c("plot","year","invasives")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_10")
AT.aov$Y2009_10

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
```

```
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_10, alternative=c("less"), paired=TRUE)

### Burn 2013 only
ATdata<-data.frame(cbind(AllTypes13only[,1:2],AllTypes13only[,9]))
colnames(ATdata)<-c("plot","year","invasives")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2010", "Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,3:4]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:2],AT.aov.3[,1],AT.aov.1[,5]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2010_11", "Y2014")

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
# 2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("less"), paired=TRUE)

### Burn 2000 and 2007
ATdata<-data.frame(cbind(AllTypes00.07[,1:2],AllTypes00.07[,9]))
colnames(ATdata)<-c("plot","year","invasives")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2009","Y2010", "Y2011")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:6]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003", "Y2009_11")
AT.aov$Y2009_11
```

```
summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

# 2003
t.test(AT.aov$Y2003, AT.aov$Y2009_11, alternative=c("less"), paired=TRUE)

# Burn 2000 and 2013
ATdata<-data.frame(cbind(AllTypes00.13[,1:2],AllTypes00.13[,9]))
colnames(ATdata)<-c("plot","year","invasives")
names(ATdata)
ATdata$year
length(unique(ATdata$plot))
ATdata$year
AT.aov.1<-data.frame(cast(ATdata, plot~year))
colnames(AT.aov.1)<-c("plot", "Y1992", "Y2003", "Y2010","Y2011", "Y2014")
AT.aov.2<-data.frame(cbind(AT.aov.1[,4:5]))
#AT.aov.2
#AT.aov.2[is.na(AT.aov.2)]<-0
#AT.aov.2
AT.aov.3<-data.frame(rowMeans(AT.aov.2,na.rm=TRUE))
AT.aov.3
AT.aov<-data.frame(cbind(AT.aov.1[,1:3],AT.aov.3[,1],AT.aov.1[,6]))
colnames(AT.aov)<-c("plot", "Y1992", "Y2003","Y2010_11", "Y2014")
AT.aov$Y2014

summary(AT.aov$Y1992)
summary(AT.aov$Y2003)
summary(AT.aov$Y2009_10)
summary(AT.aov$Y2009_11)
summary(AT.aov$Y2010_11)
summary(AT.aov$Y2014)

# 1992
t.test(AT.aov$Y1992, AT.aov$Y2003, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y1992, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
# 2003
t.test(AT.aov$Y2003, AT.aov$Y2010_11, alternative=c("less"), paired=TRUE)
t.test(AT.aov$Y2003, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
#2010_11
t.test(AT.aov$Y2010_11, AT.aov$Y2014, alternative=c("less"), paired=TRUE)
```